# Integrated Natural-Human System Modeling: A Cost-Effectiveness Analysis for Agricultural Nonpoint Source Pollution Control in Minnesota River Basin

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**Abstract**

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In the United States, there are more than 330 million acres of row crop agricultural land that produce an abundant supply of food and other products to support food security and economic development. Meanwhile, agricultural nonpoint source (NPS) pollution, most generally occurring in the absence of a landscape conservation plan, is the leading cause of water quality impairments in the rivers and streams in the United States (U.S. EPA, 2019). Voluntary incentive programs are the primary policy mechanism to improve the water quality of agricultural landscapes, employed to increase the supply of non-market ecosystem services alongside food and energy provision. This project seeks to improve the cost-effectiveness of the incentive designs by paying careful attention to both biophysical and farmers' socio-economic factors. Specifically, I 1).developed a hybrid optimization paradigm that combined the evolutionary algorithms with weighted benefit-to-cost ratio ranking to tackle the problem of spatial interdependence in multi-objective optimization; 2).identified the underlying socio-psychological drivers of farmers' intentions for conservation practices adoption, based on first-hand agricultural landowner survey data, factor analysis, and cluster analysis; and 3).estimated landowners' Willingness-to-Accept to the incentive payments and characterized their preference heterogeneity by discrete choice experiments and mixed logit modeling. The project's results enable us to identify the spatially explicit cost-efficient conservation port-

folios and analyze trade-offs/synergies among water conservation objectives under various management scenarios. Meanwhile, it advances the designs of targeted incentive mechanisms corresponding to landowners' preferences. My research integrated interdisciplinary knowledge and techniques to explore the complex natural-human system within the Minnesota River Basin for cost-efficient conservation incentive designs. The modeling framework is also transferable to other agricultural landscapes across the nation.

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# GLOSSARY

BIOPHYSICAL MODEL: a simulation of a biological system using mathematical formalizations of the physical properties of that system. Such models can be used to predict the influence of biological and physical factors on complex systems.

COMPLEXITY: features such as nonlinearity, interdependence and nonseparability of a system.

CONTINGENT VALUATION: an economic tool that uses surveys to question people regarding their willingness to pay for a good, such as the preservation of water quality.

COST-EFFICIENCY/EFFECTIVENESS: an achievement of any given level of environmental quality at lowest possible cost.

DISCRETE CHOICE MODEL: a model that specifies the probability that a person chooses a particular alternative, with the probability expressed as a function of observed variables that relate to the alternatives and the person.

ECONOMIC INCENTIVES: things that motivate you to engage in certain behavior because they are the path towards achieving your preferences.

EPISTASIS: effectiveness of a specific decision variable depends on the state of other decision variables.

EVOLUTIONARY ALGORITHM: a generic population-based heuristic optimization algorithm. It uses mechanisms inspired by biological evolution, such as reproduction, mutation, recombination, and selection.

EXTERNALITIES: effects of a market transaction that change the utility, positively or negatively, of those outside the transaction.

MARKET FAILURE: situations in which an unregulated market fails to produce an outcome that is the most beneficial to society as a whole.

MULTIPLE-OBJECTIVE OPTIMIZATION: the problem of finding a vector of decision variables which satisfies constraints and optimizes more than one objective functions. The multiple objectives are usually in conflict with each other, hence the term "optimize" means finding such a solution which gives the values of all the objective functions acceptable to the decision maker.

NPS POLLUTION: the nonpoint source pollution caused by rainfall or snowmelt moving over and through the ground. As the runoff moves, it picks up and carries away natural and human-made pollutants, finally depositing them into lakes, rivers, wetlands, coastal waters and ground waters.

PARETO OPTIMALITY/EFFICIENCY: an allocation of resources from which it is impossible to reallocate so as to make any one individual or preference criterion better off without making at least one individual or preference criterion worse off.

PREFERENCE HETEROGENEITY: the extent to which individuals tastes and preferences vary across individuals.

SUSTAINABLE DEVELOPMENT: development that meets the needs of the present generation without compromising the ability of future generations to meet their own needs. From a more ecocentric view, sustainability should also refer to maintaining appropriate levels of natural resources and ecological functions.

TRADE-OFF: a situation that involves diminishing or losing in one objective in return for gains in other objectives.

WILLINGNESS-TO-ACCEPT: the minimum amount of money that a producer (or a seller) is willing to accept to sell a good or service, or to put up with something negative, such as pollution.

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# DEDICATION

*To my parents, Jinhui and Xianghua*

# Chapter 1

# INTRODUCTION

## *1.1 Rationale*

Agricultural nutrients and other emissions such as sediment, pesticides, and animal waste remain a primary source of water quality degradation in much of the nation (U.S. EPA, 2017). Many such sources are classified as “Nonpoint Source” under the Clean Water Act (Kling, 2011a). Point source pollution comes from the fixed and readily identified sources, such as large industrial facilities and sewage treatment plants. In contrast, emissions from nonpoint sources are diffuse. In the legal definition of the Clean Water Act, point source pollution is “discernible, confined and discrete conveyance”, and the term “nonpoint source pollution” is defined to mean any source of water pollution that does not meet the definition of point source (U.S. EPA, 2019). The diffuse nature of the nonpoint source pollution makes routine observation and accurate measurement difficult and prohibitively costly. Consequently, agricultural nonpoint pollution is exempt from most federal regulations and enforceable standards but managed through voluntary compliance mechanisms (Ribaudo et al., 2008). These mechanisms have been bolstered by a number of voluntary, financial incentive programs at the federal level, but overall are characterized by the lack of significant progress in their effectiveness (Kling, 2011a).

Numerous studies in agri-environmental policy have explored a) theoretical models underlying different policy instruments that capture the essence of nonpoint source pollution (Shortle and Horan, 2002); b) the difficulties to achieve the “first-best” solutions in these policy designs associated with the characteristics of nonpoint source pollution (Xepapadeas, 2011), and c) empirical modeling techniques approximating the cost-efficient solutions in reality (Rabotyagov et al., 2010c). Shortle and Horan (2013) summarized three broad questions that need to be considered in the design of economic incentives for nonpoint pollution control: Who to target? What to target? And with what mechanism?

However, answering the three questions is nontrivial because of the characteristics of the process by which agricultural sources contribute to poor water quality. First, the diffuse nature of the emissions and the large number of small contributors challenge the task of tracing the pollutant back to their precise sources (Shortle and Horan, 2002). Moreover, the fate and transport of emissions are depended on the complex biophysical processes (such as nutrient cycling and the movement of surface water) and stochastic factors (such as weather events), which cause the complexity and uncertainty in the relationship among agricultural in-field input, the pollution output at the edge of the field, and the ambient water quality in the streams/rivers at the outlet of the watershed.

Second, the spatial characteristics of agricultural emissions affect the magnitude of the damages associated with those emissions. The distance of a given field to the flow paths, the relative downstream/upstream locations in the watershed, and the site-specific features (such as slope, soils, and cropping systems) all influence the effects of emissions to the ambient concentration of pollutants in the water body. Furthermore, the highly complex interdependence among land parcels within the watershed made the attenuation of the pollution emitted from a given field depend on the physical conditions and land conservation actions at other fields in the watershed. In other words, the abatement action in a given field can impact the effectiveness of an abatement action elsewhere in the watershed.

In addition to the characteristics of agricultural nonpoint sources, another challenge to the policymakers is imperfect information, or “information asymmetry”, about the private costs of abatement actions. Under the assumption that the goal of improving water quality as a social benefit may conflict with landowners’ private goal of profit maximization, landowners will attempt to hide their true cost information to the regulators. Although public data such as cash rental rates are commonly used for cost estimation, they only account for the opportunity cost of the land, while not include other costs such as engineering and maintenance costs. Compensation payments only based on the expected profit losses (if any) are likely to underestimate the incentives that will be needed to induce farmers to adopt conservation practices (Kurkalova et al., 2006a). The implicit costs associated with uncertainties and risks may lead farmers to demand a premium, in addition to the compensation for direct costs, to participate in the conservation programs. Meanwhile, a large body of literature shows that both direct and implicit costs (associated with uncertainty) vary by farmers characteristics, environmental factors, and other idiosyncratic farm features (Rabotyagov et al., 2014b). Thus, from the perspective of the regulators, the abatement costs heterogeneity create uncertainties about how farmers will respond to the incentive instruments. The cost heterogeneity, together with spatial interdependence, may lead the market-based policy mechanisms to fail in identifying the "first-best" allocation of emission reductions in the watershed.

In this study, I examined the policy implications of the key attributes of agricultural nonpoint pollution and abatement costs heterogeneity using a spatial explicit model of an important agri-environment region: Minnesota River Basin. The basin represents a policy-relevant setting for water quality research, as the State of Minnesota has recently announced a 25 percent water quality improvement goal by 2025, along with existing state and federally funded watershed implementation programs, with public funds being made available to meet these goals (`https://bit.ly/2UihTuy`). This project directly addresses the region's up-to-date necessities of wisely allocating social resources to meet the goal of clean water and sustainable agricultural development.

Specifically, I developed an integrated modeling framework that a) realistically incorporates the complex relationships between conservation actions and ambient water quality; b) accounts for abatement costs heterogeneity, and c) is able to approximate the cost-efficient solutions by choosing the Pareto optimal set of conservation practices and their locations in the watershed.

Over the past three decades, numerous physically-based, spatially distributed biophysical/hydrological models have been developed to simulate the effects of conservation actions on in-stream water quality. These models embrace the spatial and biophysical characteristics and can simulate the effects of combinations of land uses on ambient water quality, as well as the nonlinear fate and transport of emissions across the landscape. These hydrological simulation models, although not fully simulate everything, are generally the best tools available for social scientists to incorporate these endogenous field-level off-site impacts in their analysis. However, the spatial interdependence captured by these simulation models makes the optimization work of identifying the least cost solutions extremely difficult. Efforts at the early stage to incorporate these features into policy analysis are either simplifying the hydrological process and then solving the optimization problem via knapsack models in operation research, or using the complete hydrological simulation models only with a few selected scenario evaluation, but without explicit optimization. Rabotyagov et al. (2010c) evaluated the applications of these two approaches in detail.

The development of computer power and heuristic optimization algorithms during the past decade allows researchers to integrate system-level optimization with full biophysical models. Following Rabotyagov et al. (2010c), I incorporated biophysical simulation models with an evolutionary algorithm (EA) simulation-optimization approach to approximate the Pareto frontiers showing the least-cost combinations of conservation actions for achieving water quality improvement from multiple dimensions. In addition, to deal with the issues of spatial interdependence, I combined approaches used in exact optimization (a greedy ranking based on a weighted benefit-to-cost ratio) with EA, which can further challenge and improve the solutions and estimate trade-off frontiers which may be satisfactory in terms of policy discussion and decisions.

A large body of literature in agricultural conservation practices adoption indicates strongly that individual landowners possess fairly complex preferences over adopting a range of management practices on their land (Kurkalova et al., 2006a; Prokopy et al., 2008a). Most of the integrated modeling studies to date, whose main focus are simulation-optimization, have relied on observed behaviors with respect to the adoption of management actions (e.g., CRP adoption, conservation tillage adoption, etc.) to represent the heterogeneity in abatement costs, yet fairly strong evidence exists that the sources of cost heterogeneity are not easily observable (Key and Roberts, 2009a; Kurkalova et al., 2006a). In this project, I used landowner stated preference surveys to derive the willingness-to-accept (WTA) estimates for relevant agricultural abatement actions and to characterize the heterogeneity in individual abatement costs. Since the results of the simulation-optimization framework are tied to both the set of abatement actions and the abatement costs estimates, by carefully characterizing the sources of cost heterogeneity, one can increase the level of detail and realism of the obtained solutions from the optimization model.

## *1.2 Objectives*

In the context of agricultural sources of water quality problems, the project's overarching objective was to develop an integrated modeling framework that can be relied on to design cost-efficient incentive instruments, even in the presence of the significant complexities and uncertainties that abound in nonpoint source issues. The specific objectives of this project were:

$\mathcal{OBJ}$ 1. **Develop a hybrid optimization paradigm that facilitates the cost-efficiency of targeted incentive policy under spatial interdependence of the abatement actions.**

Fully utilizing the biophysical watershed models in optimization is valuable for the more realistic representation of the nature and spatial characteristics of agricultural nonpoint sources across the watershed. However, the spatial interdependence, where an abatement action impacts the effectiveness of an abatement action elsewhere, makes the optimization problem of identifying the least-cost solution difficult. I combined approaches used in exact optimization with simulation-optimization to explore a new way to deal with spatial interdependence in policy design. Specifically, I:

- Applied the (weighted) benefit-to-cost ratio ranking heuristic to find solutions that would have been optimal without spatial interdependence.

- Employed the solutions from benefit-to-cost ratio ranking as the starting points for simulation-optimization using evolutionary algorithms which incorporate the spatial interdependence.

- Evaluated the connection between solutions obtained from benefit-to-cost ratio ranking and simulation-optimization, and then provide the "correction factor" for spatial interdependence in policy design and implementation.

- Used the hybrid paradigm to solve the multi-objective optimization problem and find the least-cost combinations and locations of conservation practices for achieving water quality improvement targets.

*OBJ* 2. **Characterize abatement costs heterogeneity based on landowners preference heterogeneity.**

Landowners' decision about whether to enroll in a voluntary incentive conservation program is fundamentally the results of evaluating the alternatives based on their preferences and choosing the option that is most preferred. I applied a discrete choice model framework to elicit landowners' preference information for three key land conservation practices. Based on that, I estimated landowners' minimum willingness-to-accept compensation for adoption. The specific tasks for achieving this objective include:

- Conducted Minnesota River Basin landowner surveys and collected the stated preference data from discrete choice experiments.

- Applied mixed logit model to capture the individual preference variation; evaluated the effects of economics incentives and other factors on heterogeneity.

- Estimated the confidence intervals for individuals' willingness-to-accept (WTA). The estimates were then integrated into multi-objective optimization model as the information about abatement costs.

$\mathcal{OBJ}$ 3. **Develop and validate the measurement instruments to study socio-psychological attributes affecting landowners' conservation intention.**

In keeping with established literature on the presence of non-pecuniary preferences among agricultural landowners, I also studied the underlying social-psychological drivers of landowners' intentions for adopting conservation practices. Under the framework of Theory of Planned Behavior (TPB) and Diffusion of Innovation (DoI), I:

- Applied factor analysis to the landowner survey data to extract and validate the TPB & DoI attributes.

- Conducted regression modeling to explore the influences of TPB & DoI attributes on adoption intention.

- Employed cluster analysis to investigate the divergences of both socio-psychological and socio-demographic characteristics among landowners.

### *1.3 Research Questions and Hypotheses*

Three research questions guide the investigation of this project :

$\mathcal{RQ}$1. How to deal with spatial interdependence for both the optimization process and policy design?

$\mathcal{RQ}$2. How to characterize the heterogeneity of abatement costs under landowners' preference heterogeneity?

$\mathcal{RQ}$3. How to maximize water quality improvement benefits under the limited budget constraints?

Behind these three research questions are the postulates and hypotheses that define the logic of the investigation.

**Over-arching postulate:** Resources scarcity and the goal of sustainable development require Pareto optimality/efficiency in resource allocation.

▶ **Overarching hypothesis:** Cost-efficient conservation programs that target resources to activities and locations with the largest improvement in water quality for the lowest cost will improve social welfare.

**Postulate 1:** The multi-objective optimization framework provides tools for decision making based on the trade-offs among conflicting objectives in a complex system.

▶ **Hypothesis 1:** An integrated multi-objective optimization framework that incorporate biophysical model and heterogeneity in abatement costs will provide a better representation of agri-environmental policy design, and will provide a better method of calculating Pareto-optimal trade-offs among multiple objectives.

**Postulate 2:** The cost-efficient policy instruments are difficult to achieve in reality due to the complexity of agricultural nonpoint sources and the regulators' incomplete cost information.

▶ **Hypothesis 2.1:** A Simulation-optimization that fully utilizes the biophysical model and with the help of evolutionary algorithms can generate the set of approximate cost-efficient solutions .

▶ **Hypothesis 2.2:** A hybrid optimization paradigm that incorporates benefit-to-cost ratio ranking and evolutionary algorithms may find solutions that Pareto-dominate the ones from performing only benefit-to-cost ratio ranking or only evolutionary algorithms under complexity.

**Postulate 3:** Public policies that account for the environmental ramification of economic activities can internalize the externalities of the environmental goods/services and correct the market failure.

▶ **Hypothesis 3.1:** Incentive policies that provide financial compensation for implementing land conservation practices can remedy the insufficient supply of environmental goods/services.

▶ **Hypothesis 3.2:** Landowners' willingness-to-accept compensation for providing environmental goods and services depends on their preferences heterogeneity to alternative choices for their land.

**Postulate 4:** People's intentions (and behaviors) are functions of several basic socio-psychological constructs: attitude, subjective norms, perceived behavioral control, and background factors related to culture, knowledge, values, experiences, and personal needs.

► **Hypothesis 4.1:** (Positive) attitudes, subjective norms, perceived behavioral control, and past-experiences will significantly and positively influence Landowners' intentions to adopt conservation practices.

► **Hypothesis 4.2:** There are significant differences among landowner groups in terms of both socio-psychological and socio-demographic attributes.

### *1.4 Thesis Structure*

Under the guidance of the objectives and research questions, the following part of the dissertation is organized into three standalone articles and a synthesis conclusion.

In Chapter 2, I focused on addressing *Objective 1*. I presented a hybrid optimization paradigm where benefit-to-cost rankings and evolutionary algorithms are integrated to solve a multi-objective optimization problem with epistasis (i.e. spatial interdependence) embedded in a biophysical simulation model. My application utilized a variety of landscape conservation actions to assess tradeoffs for sediment reduction and wildlife conservation objectives in the Le Sueur River watershed, one of the major watersheds in the Minnesota River Basin.

In Chapter 3, I focused on addressing *Objective 3*. Based on the Theory of Planned Behavior (TPB) and Diffusion of Innovation (DoI), I developed the measurement instruments to investigate the influence of TPB & DoI attributes on landowners' intentions to adopt conservation practices. Meanwhile, I explored the heterogeneity in terms of both the socio-psychological and socio-demographic features among different landowner clusters within the Minnesota River Basin.

In Chapter 4, I focused on addressing *Objective 2*. I analyzed data from the stated preference survey to reveal landowners' preference heterogeneity and derived WTA estimates for land conservation practices. I also scaled the WTA estimates up to the county-level and subbasin-level so that they could be reasonably coupled with a regional-specific biophysical model for benefit-cost analysis and optimization simulation.

In Chapter 5, I closed with concluding remarks and perspectives on future research.

## *1.5 Related Publications*

- Lang Z., Rabotyagov S., Cho S., Campbell T., Kling C., 2020. Good Seeds Bear Good Fruit: Using Benefit-to-cost Ratios in Multi-objective Spatial Optimization under Epistasis. *Land Economics 96(4): 531-551.*

  This paper contributes to Chapter 2.

# Chapter 2

# GOOD SEEDS BEAR GOOD FRUIT: USING BENEFIT-TO-COST RATIOS IN MULTIOBJECTIVE SPATIAL OPTIMIZATION UNDER EPISTASIS

## *2.1 Abstract*

Many biophysical models exhibit epistasis, where a conservation action impacts the effectiveness of a conservation action elsewhere. Heuristic methods (e.g., evolutionary algorithms), integrating biophysical models into optimization, have found productive use for dealing with such issues. At the same time, ranking conservation actions according to the benefit-to-cost ratios continues to be used mainly for its simplicity and ease of interpretation. In our application, we employ a hybrid method where solutions, obtained via benefit-to-cost rankings, serve as starting points for an evolutionary algorithm (EA) employing a biophysical model. Our application utilizes a variety of landscape conservation actions, including wetland restoration, working land conservation options, and in- and near-channel conservation options to assess tradeoffs for sediment reduction and wildlife conservation objectives in the study watershed (Le Sueur River Basin, Minnesota, USA). We find that for the particular type of epistasis represented by the sediment model, the weighted benefit-to-cost ratio-derived solutions perform remarkably well.

Most (90% rate) of the solutions based on a simple weighted benefit-to-cost ratio ranking remain in the Pareto frontier. While the use of an EA finds additional Pareto-nondominated solutions not generated by the simpler ranking method, we find it to be a fairly robust option for generating cost-efficient patterns of conservation actions. However, full model simulation is still needed to translate the effects of such patterns on watershed-level outcomes. We further find that an EA heuristic in our application performs poorly without seeding by the

benefit-to-cost ratio-derived solutions.

## *2.2 Introduction*

Optimizing the mix and location of conservation actions within a watershed, which considers the spatial heterogeneity in conservation effectiveness and cost across the agricultural landscape, can bring significant gains in terms of prioritizing conservation funds and is a necessary component for any effort aiming to fully assess or maximize the net social benefit of managed landscapes. Effectiveness of conservation actions is, among other factors, highly dependent on their spatial arrangement within a watershed. The structure of many biophysical models captures such effects, and models are often used in optimization applications within a simulation-optimization paradigm. Traditional mathematical programming techniques such as dynamic programming, linear programming and nonlinear programming are well-known methods to solve multi-objective optimization problems. However, in large and highly nonlinear models, these algorithms can fail to find feasible solutions, or be trapped in local optima (Cai et al., 2001). In recent years, evolutionary algorithms (EAs) have been widely applied to water resources research because of their flexibility and effectiveness for optimizing complex systems (Olofintoye et al., 2013; Reddy and Kumar, 2006). A sizeable body of literature on agricultural landscape optimization using evolutionary algorithm (EA) simulation-optimization approaches has been developed, with perspectives emphasizing agricultural systems engineering (Veith et al., 2003; Arabi et al., 2006; Maringanti et al., 2011); agricultural and environmental economics (Bostian et al., 2015; Rabotyagov et al., 2013), and hydrology (Wu et al., 2018). In the context of cost-efficiency, where environmental objectives are not monetized, the task is generally to find a spatial pattern of conservation actions that attains a specific environmental objective with the lowest cost (or a pattern which attains the largest desirable environmental change for a limited budget). Often, multiple non-commensurate environmental objectives are of importance, and the cost-effectiveness problem is generalized into multiobjective optimization, where the principle of Pareto-efficiency is used to generate solutions (i.e., one cannot attain any improvement in a desirable objective (e.g., lower cost) without a sacrifice of another desirable objective (e.g., water quality)). In other words, such optimization exercises aim to construct frontiers of production possibilities with respect to 1) non-monetized goods and services represented by environmental objectives and 2) monetized goods and services represented by the costs of conservation actions.

In some cases, conservation budgets or environmental targets represent stringent real-world requirements, and constrained optimization becomes of primary importance. In other cases, the question of interest is not specifically tied to a precise water quality goal or budget constraint; rather, the primary interest lies in understanding the tradeoffs between cost and one or more environmental objectives or in assessing the degree of synergistic relationships among environmental objectives. Synergies may be present among those environmental objectives, which can be produced simultaneously by some conservation actions and/or a particular spatial arrangement of conservation actions. We do not impose strict constraints on costs or environmental objectives and estimate the full scope of cost-efficient tradeoffs and potential synergies.

In this paper, we focus on estimating efficient tradeoffs between multiple environmental and economic objectives using a hybrid simulation-optimization approach. Sediment reduction, a common non-point source water pollution management problem, constitutes the first environmental objective, with wildlife production (represented by estimates of duck hatchlings[1]) being the second. Since the number of breeding ducks is driven primarily by the abundance of habitat, we expect synergies in the benefit dimension for conservation practices such as wetland restoration. We use highly spatially resolved data for the study region, an area of intensive crop production, aiming to estimate tradeoffs and to present the solutions in a spatially explicit way. We employ a multiobjective evolutionary algorithm (EA) heuristic to estimate the set of Pareto-efficient landscape management configurations. On the environmental benefits side, we use an ecohydrologic sediment model tailored to the

[1] We estimated duck hatchlings for five duck species: mallard, gadwall, blue-winged teal, northern pintail, and northern shoveler

study region and a simple empirical model of duck production. On the costs side, we use a mix of engineering, econometric, and real options estimates to arrive at costs associated with conservation actions to be used in optimization.

Our landscape-level watershed optimization problem is formulated with many decision variables corresponding to small spatial units and coupled with a complex biophysical simulation model. Due to the "curse of dimensionality", it is not feasible to solve such simulation-optimization problem exactly (see, e.g.,Kollat et al. (2008b)). Consequently, we explore an alternative. We combine approaches used in exact optimization (a "greedy" ranking based on a weighted benefit-to-cost ratio) with a simulation-optimization EA heuristic which can further challenge and improve the solutions and estimate tradeoff frontiers which may be satisfactory in terms of policy discussion and decisions. Intuitively, there is a tradeoff in error to be considered in choosing the optimization approach. Heuristic simulation-optimization approaches represent the consequences of landscape actions in a manner exactly consistent with process model assumptions, but we cannot be assured of the optimality of solutions obtained. Exact approaches assure us of optimality of the solutions obtained yet introduce error due to the simplification of the underlying process (model). By combining approaches we seek to reduce the overall error associated with optimization (of course, any errors associated with the process model and its assumptions still propagate to any solutions discovered). At a minimum, such frontiers can provide an estimate of how well a specific watershed policy proposal compares to the solutions such hybrid approaches can feasibly discover.

We start with a simple multiobjective optimization problem, and then briefly discuss the notion of epistasis in relation to biophysical models in particular. We then present the well-known benefit-to-cost ratio ranking heuristic which, under some conditions, produces exact members of the optimal trade-off frontier. We then discuss the hybrid approach, expressed as the EA "seeding" paradigm. We demonstrate an application of our approach to a particular study area (which shares common characteristics with many watersheds of interest to nonpoint source pollution management community) and conclude with suggestions for future work.

## 2.3 Methods

### 2.3.1 Multiobjective Optimization

We estimate the efficient tradeoffs by conducting a multiobjective optimization search using the EA heuristic. The objective is formulated similarly to Rabotyagov et al. (2010a): we aim to approximate the Pareto-frontier associated with simultaneously minimizing (1) the annual cost of conservation actions affecting sediment and duck production; (2) the mean annual sediment load at the watershed outlet, and (3) the (negative of) total annual duck hatchling production. That is, the algorithm solves:

$$\min \left[c(\boldsymbol{X}), y(\boldsymbol{X})^1, y(\boldsymbol{X})^2, ..., y(\boldsymbol{X})^N\right] \tag{2.1}$$

subject to $(\boldsymbol{X}, \boldsymbol{Y}) \in T$, where $\boldsymbol{X}$ is a set of conservation actions. The environmental benefits of $\boldsymbol{X}$ are denoted by $\mathbf{Y}$, where $\mathbf{Y}$ is a vector with $N$ elements, i.e., $\boldsymbol{Y} = (y^1, y^2, ..., y^N)$. Here, $N = 2$, and the relevant environmental indicators are the sediment loadings and duck hatchlings. $T$ defines implicit constraints represented by the environmental models. The total cost of a particular pattern of conservation actions is represented by $c(\boldsymbol{X})$.

The set of solutions consists of all watershed conservation plans that are Pareto - optimal. A conservation plan $\boldsymbol{X}$ is Pareto-optimal if there is no $(\boldsymbol{X}', \boldsymbol{Y}') \in T$ such that $y(\boldsymbol{X}')^n \leq y(\boldsymbol{X})^n$ and $c(\boldsymbol{X}') \leq c(\boldsymbol{X})$, for all $n \in \{1, 2, ..., N\}$, and such $m \in \{1, 2, ..., N\}$, such that $y(\boldsymbol{X}')^m < y(\boldsymbol{X})^m$ or $c(\boldsymbol{X}') < c(\boldsymbol{X})$. In other words, once such a solution is found, it is not possible to improve on any one objective without trading off another. All the (approximate) efficient solutions found make up the three-dimensional trade-off frontier, which we denote as $\boldsymbol{\mathcal{F}}(\boldsymbol{X})$. The EA used is an elitist (non-dominated solutions are maintained in the archive) (Rabotyagov et al., 2010a) modification of a SPEA2 algorithm (Zitzler et al., 2001)[2]. In our application, we assume that the $K$ decision variables are binary, the cost objective is linear and separable ($c(\boldsymbol{X}) = \sum_{k=1}^{K} c_k x_k$), the duck population objective is also linear and

[2]We used a C++ library of genetic algorithms GALib version 2.4.6 (Wall, 2006) to implement the evolutionary search algorithm.

separable ($y^{ducks}(\boldsymbol{X}) = -\sum_{k=1}^{K} g_k x_k$). The sediment objective is represented by the sediment simulation model which is not easily written down in a compact form: $y^{sed}(\boldsymbol{X}) = S(\boldsymbol{X})$.

### *2.3.2 Epistasis*

In many problems where simulation models are used, effectiveness of a specific decision variable depends on the state of other decision variables. Such issues often arise in biological conservation and other environmental management problems. For example, the survival probability of a species depends on the overall habitat size, the configuration of sites, and the distance and connectivity between sites (Fahrig, 2003), so the number of species protected by a particular parcel of habitat may well depend on whether the parcel is connected to other parcels of habitat or is relatively isolated (Murdoch et al., 2007). Given that everything else being equal, contiguous patches tend to have a higher ecological value than isolated ones because species can disperse between sites, facilitating recolonization of sites in which a population has become extinct (Hanski, 1998). As Murdoch et al. (2007) pointed out: "...in virtually all cases of interest, conservation actions are not independent of each other, and conservation planning is, therefore, a 'portfolio allocation' problem rather than a simple ranking problem: the benefits or costs of an action depend upon what other actions are taken." As a result, one of the challenges in cost-effective policy design for biodiversity conservation is that the ecological value of habitat patches for the survival of species is space dependent,i.e. it depends on the presence and location of other habitat patches Drechsler and Wätzold (2009). When returns are not independent across actions, the complete allocation across all actions needs to be considered jointly rather than considering the return on each action in isolation. A recent study by Taylor et al. (2019) highlighted that policies for wildfire risk mitigation depended on the character of the spatial dependencies between neighboring homeowners' investments. Murdoch et al. (2007) showed examples that the number of species protected by purchase of a particular parcel of habitat might well depend on whether the parcel was connected to other parcels of habitat or was relatively isolated. As he emphasized: "...when returns are not independent across actions, the complete allocation across all actions needs to be considered jointly rather than considering the return on each action in isolation."

In nonpoint source water pollution problems, this is driven largely by hydrologic interactions, and previous work variously referred to such effects as "endogeneity" (Carpentier et al., 1998; Khanna et al., 2003), "nonlinearity" (Rabotyagov et al., 2014a; Shortle and Horan, 2013), "interdependence" (Randhir et al., 2000; Murdoch et al., 2007), and "non-separability" (Rabotyagov et al., 2014a) or "epistasis" (Maier et al., 2014; Kollat et al., 2008a). As an example, in Appendix A.6, we provide a derivation of the gamma-distributed routing hydrographs in a cascade of linear reservoirs system. From the derivation, one can see that the effect of placing a reservoir is dependent on the presence or absence of other reservoirs in the cascade. We discuss the similar underpinnings of interdependence in our sediment model below and present a simulation example demonstrating the magnitude of these effects in our model in Appendix A.6.

Given EAs inspiration by biology, and following (Kollat et al., 2008b), we adopt the term "epistasis" to refer to the potential interdependence across actions since the term is used to describe "a phenomenon whereby the effects of a given gene on a biological trait are masked or enhanced by one or more other genes" (Moore and Purugganan, 2005). More broadly, one can speak about epistasis in terms of positive or negative externalities resulting from an action which affects the production possibilities elsewhere. Strong epistasis can drastically complicate market-based schemes for water quality trading (e.g., Shortle and Horan (2013)). Rabotyagov et al. (2014a) discuss this issue but suggest that a nonpoint source water quality trading scheme can still be useful when epistasis is ignored, while Kuwayama and Brozović (2013) present a more complicated trading mechanism explicitly designed to deal with epistasis present in trading groundwater, as hydrology provides for strong interdependence between decisions in the system.

Epistasis (interdependence) across decision variables has received a fair amount of attention in the broader field of evolutionary computation (Chen and Rajewsky, 2007; Kollat et al., 2008b; Li et al., 2016). Sun (2017) suggests new methods of identifying interactions and improving optimization algorithms. Undoubtedly, such approaches may prove very useful, but in the current application, we essentially treat the objective function represented by a biophysical model as a "black box" (but see Wu et al. (2018) for an example of trying to "unpack" the structure of an ecohydrologic model).

In general, the presence of epistasis results in situation where the environmental benefit is not well represented by aggregating incremental changes, even when the incremental changes account for the differential impact of individual actions on the environmental objective. For instance, in this application, outlet sediment is not characterized by the sum of incremental reductions in sediment: $S(\boldsymbol{X}) \neq S_0 - \sum_{k=1}^{K} b_k x_k$, where $S_0$ represents the sediment baseline and $b_k = S_0 - S(x_k = 1; x_{-k} = 0)$ represents the estimated incremental sediment reduction benefit obtained by running the sediment model selecting one conservation action at a time, keeping all other candidate conservation sites at their baseline values.

### *2.3.3 Weighted Benefit-to-Cost Ranking (wBCR)*

Meanwhile, consider a simple multiobjective optimization problem, where the decision-maker wishes to choose $n$ binary decision-making units $x$, in order to

$$\min(-\sum_{i=1}^{n} b_i x_i, -\sum_{i=1}^{n} g_i x_i, \sum_{i=1}^{n} c_i x_i) \tag{2.2}$$

subject only to the requirement that all $x \in \{0, 1\}$, where $b_i$ represents an independent sediment reduction ability benefit from a candidate site, and g is the duck hatchling coefficient. Suppose one were to construct an index, for each $x_i$, where $\lambda$ is the weight place on the sediment objective: $r(x_i) = \lambda \frac{b_i}{c_i} + (1 - \lambda) \frac{g_i}{c_i}$, $\lambda \in \left[0, 1\right]$, and sort this index in a descending fashion to obtain an ordered list and a corresponding ordered list of decision-making units $x_{r(k)}$, where, for example, $x_{r(2)}$ denotes the decision-making unit with the second-largest index $r$. A corresponding decision vector

$$X_k = \{x_{r(1)}, x_{r(2)}, ..., x_{r(k)}, ..., x_{r(n)}\} = \{1, 1, ..., 1, 0, ..., 0\}$$

is then created. It has been known for some time (Cohon and Marks, 1975) and it is easy to show (see Appendix A.1) that $\boldsymbol{X}_k$ is a member of the Pareto-front associated with the objective function. In other words, one can show that there does not exist another decision vector which Pareto-dominates $\boldsymbol{X}_k$ (although other Pareto-efficient solutions may exist). We will refer to this procedure as weighted benefit-to-cost ratio, or wBCR. Note that such procedures are referred to as "greedy", especially in relation to single- and multi-objective knapsack problems (see, e.g., Lust and Teghem (2012) and Schulze (2017)). Existence of hard constraints (for example, with respect to cost) distinguishes knapsack problems from the problem we are considering, where the 'granularity' of decision variables (potential conservation sites) is small enough that going down the list of wBCR solutions presents a fairly dense tradeoff frontier and a watershed planner either can either find a point on the frontier fits their budget (or attains the environmental goals) closely enough or alternatively is only really concerned with identifying optimal tradeoffs. Duke et al. (2013) confirmed the optimality of simple benefit-to-cost ratio ranking for 2-objective problems of landscape optimization with high granularity and linear and separable objective functions.

It is easy to imagine that the presence of epistasis may invalidate the efficiency of the wBCR ranking procedure. For example, consider a "benefit" function such that $B(x_j = 1; x_k = 1, ...) = B(x_j = 0; x_k = 1, ...)$ but $\frac{b_j}{c_j} > \frac{b_k}{c_k}$ (where incremental benefits are estimated using the 'one-at-a-time' procedure) so that $x_j$ gets selected first according to the benefit-to-cost ranking. Yet, if a decision-maker decides to proceed down the list of ranked decision variables so that $x_k$ is selected, unselecting $x_j$ would represent a strict Pareto-improvement, meaning that a wBCR solution cannot be efficient. In other words, an action which was best given that some other action was not selected may no longer be efficient. A connection with hysteresis, or path-dependence, can clearly be made in this case, but we leave the discussion of path-dependence in watershed optimization for future work.

Three potentially important questions emerge. *First*, to what degree is the simulation model epistatic in the sense that "the whole is not the sum of its parts"? In the applied watershed management or policy context, the interest is often in assigning *separable* benefits associated with a particular conservation action. As discussed in Kling (2011b) and Shortle and Horan (2013), separating the ‘abatement’ benefits in such a manner facilitates the design and implementation of the traditional policy tools such as taxes, subsidies, or trading systems. However, the presence of epistasis may lead to such policies being inefficient or ineffective in the sense that pollution reduction may either be under- or over-estimated. If epistasis is present, is there a consistent pattern which may be used in subsequent policy design? Is the nature of interdependence essentially one of negative interactions or is there a possibility of positive interactions (which can be thought about as synergies in conservation effort)?

*Second*, although the presence of epistasis can invalidate the Pareto-efficiency of wBCR approaches, it need not do so. In that case, wBCR approaches (and the particular case of benefit-cost ratio ranking in two dimensions) as presented in numerous existing research (Feng et al., 2006; Murdoch et al., 2007; Ran et al., 2013; Duke et al., 2013) may still hold significant optimization, interpretability, and policy design value, even when complex (and epistatic) simulation models are used.[3]

*Third*, what is the relationship between wBCR and EA approaches? Does the use of wBCR have the potential to improve the performance of EA in realistic applications with very large search spaces? And, in turn, can the EA build upon the optimization logic embedded in wBCR but improve upon wBCR solutions by exploiting the epistatic structure of the simulation model? The first part of the question relates to the notion of “seeding” the EA with a priori known or otherwise obtained members of the Pareto-front. Resent examples of using “good seeds” in multiobjective EAs include Hernandez-Diaz et al. (2008); Truemper (2016) and Friedrich and Wagner (2015). The basic intuition is that EAs are in a sense “blind” and the human researcher can use logic, specific domain knowledge, and other mathematical approaches to pass to the EA an “intelligent paradigm (see Truemper (2016)) which can steer the EA in the right direction and improve its performance. The consensus

[3]For an applied conservation example, see tradeoffs developed in wBCR fashion by B. Bryant and C. Weil at `https://charlottegiseleweil.github.io/webviz_natcap/intro.html`

in the literature is that if one is able to bring a good set of initial solutions as seeds in the EA population, the EA performance is typically improved by a non-trivial amount (Friedrich and Wagner (2015)), with Bi et al. (2015) showing it in an applied water resources context.

The answer to the first question (on the nature of epistasis) in large part guides the likely answers to the questions on whether wBCR approaches can still be directly useful for optimization and policy design (second question) or whether the construction of solutions based on wBCR can be useful as starting values for EA optimization (third question). Although the simulation models may be complex and not lend themselves easily to comparative static analyses, the domain of these models and their theoretical underpinnings can provide a great deal of insight. As a thought experiment, consider a somewhat contrived example of selecting household chemicals for cleaning. Both bleach and vinegar can be used separately (and could be assigned separate benefit-to-cost ratios), yet one should never choose one of these chemicals given that the other one is being used in order to avoid the production of noxious gas [4].In this case, the magnitude of the interaction is large enough to turn the benefit of an isolated option negative. In such cases, constructing benefit-to-cost ratios based on separate estimates of benefits is not useful. Most interaction effects in conservation or nonpoint source pollution problems are expected to be bounded so that the main effect of a conservation action could potentially be driven to zero but is not likely to be negative. Exceptions could be envisioned in cases where the site of a conservation action may become a pollution source depending on other actions in the watershed. (examples may include the changes in production of GHG methane (Zhang et al., 2017) or toxic methylmercury in restored wetland (Strickman and Mitchell, 2018; Metcalfe et al., 2018)). Such possibilities should be elucidated at the outset by biophysical component modelers and should help guide the expectations regarding the utility of wBCR approaches. In our application, the model structure does not allow for either "catastrophes" or "magic bullet" solutions for either sed-

[4] As explained, for example in https://www.goodhousekeeping.com/home/cleaning/tips/a32773/cleaning-products-never-mix/. Of course, many other examples of fairly dramatic epistatic effects can be offered. The common feature is the degree of importance of taking the whole-system perspective.

iment or wildlife. The scale of locations represented by decision variables is small and we do not expect any one location to have a major impact on the effectiveness of actions at other locations. Given these considerations, we conjecture that the nature of individual-level epistatic effects in our application is small so wBCR procedure is likely to prove useful. Given the number of decision variables and the structure of the simulation model, we expect that adopting the intelligent paradigm of seeding the EA with wBCR-derived solutions is likely to improve the performance of the simulation-optimization heuristic. At the same time, it is not a priori clear whether the wBCR-derived solutions can withstand the challenge by EA iterations so the direct policy relevance of wBCR ranking is a more open question.

## 2.4 Empirical Application

### 2.4.1 Study Area

The Le Sueur River watershed, located in south central Minnesota, is one of the twelve major watersheds in the Minnesota River Basin. Ecological health and aesthetics of the Minnesota River and its tributaries are affected by excess suspended sediment, measured as total suspended solids (TSS) (Belmont et al., 2011b; Schottler et al., 2014). An increased TSS results in higher water turbidity, lower light penetration, and, consequently, bloom of undesirable floating algae, causing degradation of aquatic habitats, loss of biodiversity, and impairment of aesthetic quality. The water quality issues have been exacerbated in the past 150 years due to an ongoing expansion of cropland and altered watershed hydrology (Belmont et al., 2011b; Gran et al., 2011). For example, sediment in Lake Pepin, a naturally dammed lake on the mainstem Mississippi River, downstream from its confluence with the Minnesota River, has increased by an order of magnitude since 1830 CE (Engstrom et al., 2009), with 90% of the loads originating from the Minnesota River. Further, the Le Sueur watershed, as part of the Prairie Pothole Region, is an important habitat for waterfowl, but with the expansion of cropland and conversion of habitat to agricultural fields, the populations of some species have suffered a decline (Reynolds et al., 2001).

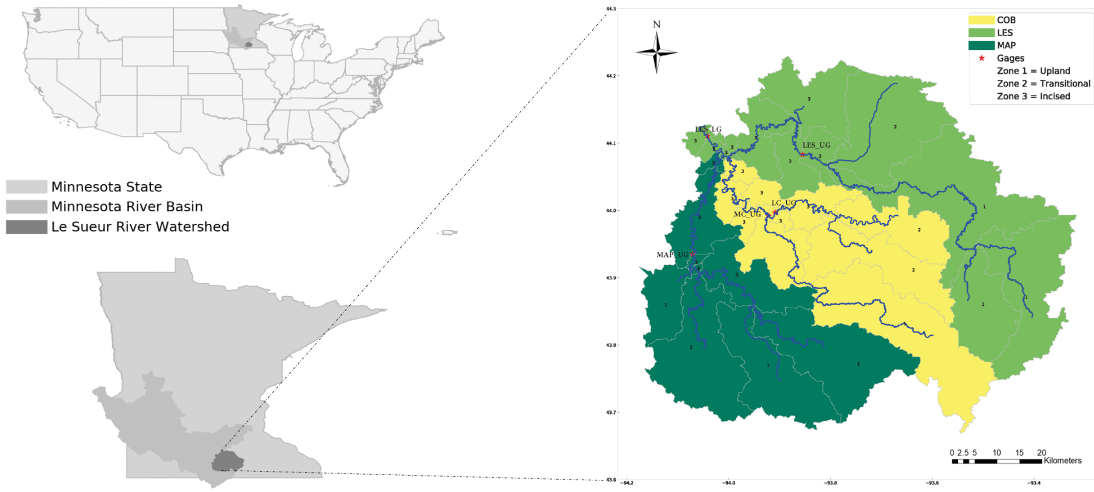


Figure 2.1: The Le Sueur River Basin (LSRB) consists of three subwatersheds (Le Sueur (LES), Cobb (COB), and Maple (MAP)), in which three geomorphic zones (1=upland, 2=transitional, and 3=incised) are defined. MOSM simulates sediment loading at five gage locations, three above the knick points (Maple near Sterling Center ($MAP_{UG}$), Little Cobb ($LC_{UG}$), and Le Sueur at St.Clair ($LES_{UG}$) and one below the incised zone (Le Sueur below the confluence with the Maple and Cobb Rivers ($LES_{LG}$).

There are over 30 lakes in the Le Sueur river watershed with 1200 miles of streams, including the Maple, Cobb, and Little Le Sueur Rivers (Kudelka, 2010). The Le Sueur river watershed is mostly rural, with 82% of the land under agricultural cultivation (MPCA 2012). The watershed is the largest contributor of sediment to the Minnesota River, delivering up to 30% of the river's annual sediment load, although it drains only 6% of the basin area (about 1,112 square miles) (Boettcher, 2015).

### *2.4.2 Models: Sediment Model*

To model the effect of conservation actions on sediment reductions, we use a watershed simulation model("Management Options Simulation Model (MOSM)") developed by Cho et al. (2019). MOSM simulates the movement of water and sediment across a watershed and evaluates the effects of various management options on sediment delivery and loading. It is a reduced-complexity model, where many components (i.e., spatial and temporal grids, and number of interacting state variables) and the degree of complexity (i.e., range of physical, chemical, and biological processes) have been reduced to include only those processes essential to represent the sediment transport and surface water routing. MOSM is data-driven, where it distributes the results of the physical processes from observed data, and its structure and predictions are constrained by the best-available existing information, including stream gaging records, an integrated watershed sediment budget, historical trends in the watershed processes, and independent measures of outputs, such as sediment fingerprinting and a suite of geomorphic change detection outputs.

MOSM consists of two computational modules: hydrologic routing, and sediment delivery and loading with a set of management options, addressing agricultural field erosion, water conservation, and near-channel sediment loading (Table 2.1).

*Second*, MOSM utilizes a high-resolution topography through Topofilter simulation (Cho et al., 2018) to estimate the on-field and in-stream sediment delivery ratios (SDR) and loading across the watershed by integrating spatially-distributed information about soil loss to the integrated sediment loading at the watershed outlet. Sediment delivery and loading module evaluates the effects on sediment delivery and loading from (1) reducing soil erosion with Tillage Management Option (TLMO); (2) reducing sediment delivery on field with Agricultural Field Management Option (AFMO), WCMO, and Buffer Management Option (BFMO); and 3) reducing near-channel source erosion with Ravine Management Option (RAMO) and Near-Channel bluff Management Option (NCMO) (Table 2.1). For more information about MOSM, refer to Cho et al. (2019).

MOSM, although a reduced-complexity model, is nevertheless expected to exhibit epistatic behavior in relation to the management options which affect water storage. As described in Cho et al. (2019), daily peak flow control is key to reducing in-channel-generated sediment, and field and in-channel water storage can accomplish this goal by both direct attenuation and delay (e.g., NRCS Hydrology Engineering Handbook and Appendix A.6).

The conceptual source of epistasis in our sediment model is hydrologic interdependence of

Table 2.1: Various management alternatives are grouped into Management Option (MO) types according to sediment sources and mechanisms of sediment loading reduction

| MO Types | Description | Location of implementation | Example management practices |
|---|---|---|---|
| Tillage MO (TLMO) | Crop production and tillage management | Field | Conservation tillage, reduced tillage, conventional tillage |
| Agricultural Field MO (AFMO) | Field erosion management | Field | Grassed water ways |
| Water Conservation MO (WCMO) | Field water storage to attenuate peak river discharge | Field | Water Retention ponds, wetland restoration |
| In-channel Water Conservation MO (ICMO) | In-channel water storage to attenuate peak river discharge | Channel | Temporary water storage in channel |
| Buffer MO (BFMO) | Vegetation planting near channel | Field near channel | Buffer strips |
| Ravine MO (RAMO) | Ravine tip stabilization to reduce branch growth | Ravines | Ravine tip stabilization |
| Near Channel MO (NCMO) | Bluff erosion management | Bluffs | Bluff stabilization, toe protection |

water-storing features along hydrologic flow-paths in the watershed, especially as it manifests itself in reductions in peak flows (main physical driver of near-channel sediment in our model). In Appendix A.6, as an example of how sequential water reservoirs reduce (and delay) peak flows, we include a "classic derivation" (in the words of Hansen et al. (2003)) in hydrology which shows that the effect of placing a reservoir in a flow-path depends on the presence of other reservoirs upstream or downstream.

### *2.4.3 Models: Wildlife Model*

For the wildlife objective of increasing waterfowl populations, we used a modification of the model recently used by the USDA to estimate economic benefits of wetland conservation in the Prairie Pothole Region. The model for estimating duck hatchlings (H) affected by wetland restoration options (WCMO) is a function of the nesting pairs (NP), nest success (NS), re-nesting propensity (NI), and clutch size (CS) (Hansen et al., 2015) :

$$H = \mathrm{NP} \times \mathrm{NS} \times \mathrm{NI} \times \mathrm{CS} \tag{2.3}$$

where NP is affected by wetland size and location (see Equations A.10, A.11), and NS is affected by wetland location and the grassland area surrounding a restored wetland (see Equations A.12, A.13).

An additional factor, should one be focused on adult duck numbers, would be the one associated with survival from hatchlings to adult ducks (referred as the reproductive success). It contains two aspects: the survival from hatching to fledging and the postfledging survival to recruitment, which is often measured by the number of offspring that enter the breeding population (Dzus and Clark, 1998). We do not have good estimates of reproductive success for all the duck species in our study, but we note that for black ducks, according to the results from Ringelman and Longcore (1982), young ducklings had a survival rate of 0.6073, which was significantly lower than the 0.6988 rate for older ducklings. The total brood survival was estimated at 81% (Ringelman and Longcore, 1982). Hatchling numbers for other species could then can be easily adjusted, given the appropriate estimate of reproductive success.

Using existing nesting pair and nest success models, as well as field survey data (Reynolds et al., 2006; Mayfield, 1975; Reynolds et al., 2001; Baldassarre, 2014) allows us to generate estimates of these parameters for the five duck species (mallard, gadwall, blue-winged teal, northern pintail, and northern shoveler) in the Le Sueur River Watershed (Details about the model can be found in Appendix A.3).

We should note that the model as outlined by Hansen et al. (2015) has the potential to be epistatic, as it takes, as its input, the grassland area surrounding a restored wetland (WCMO) (see Equation A.12 in Appendix A.3). To the extent that some other MO in our model may alter grassland area (e.g., WCMO, AFMO, BFMO), the grassland area becomes itself endogenous and induces epistasis in the model. However, the effect of surrounding grassland area is of secondary importance in the duck production model and in this paper, we abstract from this issue and use the model as non-epistatic, and linear and separable in the discrete WCMO adoption decision variables.

## 2.5 *Optimization and Seeding*

### *2.5.1 Cost Assumptions*

For the management options simulated, we largely maintain the cost assumptions developed by Cho et al. (2019), modifying those in two ways. First, based on Wade et al. (2016) econometric estimates of costs of tillage adoptions, we use \$15/acre/year as the assumed cost of Reduced Tillage, and \$30/acre/year as the assumed cost of Conservation Tillage management options. Those costs were used for the 4,626 TLMO candidate sites in the watershed. Second, for the cost of agricultural land conversion (relevant for AFMO, BFMO, and WCMO options), we use area-specific real options estimates reported in Schroder et al. (2018). (Table 2.2). For the installation and management costs of the remaining MOs, we used the estimates reported in Cho et al. (2017) (Table 2.3).

Table 2.2: Land conversion costs

| County | $P^{NPV}$(\$/acre) | $P^{*}$(\$/acre) |
|---|---|---|
| Blue Earth | 282 | 312 |
| Faribault | 369 | 375 |
| Freeborn | 433 | 440 |
| Steele | 281 | 307 |
| Waseca | 358 | 364 |

Table 2.3: Number of candidate options and their installation and maintenance costs

| Management options (MOs) | Number of candidate sites | Installation Costs(\$/acre) | Maintenance Costs(\$/acre) |
|---|---|---|---|
| AFMO | 2,119 | 3,200 | 64 |
| BFMO | 517 | 1,000 | 45 |
| WCMO | 7,874 | 3,000 | 574 |
| ICMO | 537 | 250 | 1.4 |
| RAMO | 106 | 6,000 | 35 |
| NCMO | 1,112 | 200 | 0.7 |

### *2.5.2 Creating Seeds*

We estimate the incremental benefit from each of the modeled management options (MOs) by running the simulation model one MO at a time (for each of 16,891 MOs simulated) and computing the estimated sediment reduction benefit and the duck hatchling increase. Most of our MOs are formulated as binary decisions, with the exception of tillage, where both Reduced Till and Conservation Till represent available conservation actions at cropland polygons in the watershed. For TLMO genes, the model was run on Reduced Tillage and Conservation Tillage, and those options were ranked using a benefit-to-cost ratio first. Uniformly, Reduced Tillage was a more efficient option, and a binary decision of continuing with baseline Conventional Till or adopting Reduced Till was left for the ranking procedure's consideration. For each gene and a weight on sediment reduction, $\lambda$, ranging from 0 to 1 in increments of 0.1, a weighted benefit-to-cost ratio was computed, and scaled by multiplying it by 1,000 to avoid very small numbers. As a result, the ratio is expressed in kg/year of sediment reduction, and in 1 duck hatchlings per dollar. The results were sorted for each $\lambda$ in descending order. To create solutions based on wBCR, we selected top genes for each weight in increments of 100, assigning a "select" gene encoding to the top locations. The procedure resulted in 1,848 seeds being used.

### *2.5.3 EA Frontiers*

Using the EA multiobjective optimization heuristic, we estimated three Pareto-frontiers, running the algorithm to the consolidation ratio (share of solutions in the undominated archive looking 10 generations back present in the current generation) of 0.99 (Goel and Stander, 2010).

The first ($\boldsymbol{\mathcal{F}}_0$) started with a population of randomly generated solutions and did not incorporate any seeds which utilize domain-specific information or any sort of "intelligent paradigm". The second frontier ($\boldsymbol{\mathcal{F}}_{unif}$) included seeds which represented: a zero cost baseline scenario, an "everything, everywhere" scenario, and solutions representing a uniform

Table 2.4: EA Pareto-frontiers

| Frontier | Number of individuals in the final frontier | Number of generations (iterations) to convergence (consolidation ratio of 0.99) | Optimization log name and location |
|---|---|---|---|
| $\mathcal{F}_0$ – no seeding | 1,342 | 15,995 | MOSM 2018-04-30 1248 SPEAMO https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi%3A10.7910%2FDVN%2FQPESTS |
| $\mathcal{F}_{unif}$ – seeding with uniform application of all MOs, plus a zero cost baseline and an "everything, everywhere" scenario | 4,406 | 1,576 | MOSM 2018-04-30 2110 https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi%3A10.7910%2FDVN%2FLT7GD1 |
| $\mathcal{F}_{unif+wBCR}$ — seeds in the $\mathcal{F}_{unif}$ and wBCR seeds | 2,369 | 216 | MOSM 2018-04-30 1610 https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi%3A10.7910%2FDVN%2FLFSSOZ |

application of each of MOSM MOs to the available candidate sites. The third frontier, $\mathcal{F}_{unif+wBCR}$, used the 1,848 wBCR seeds in its initial population, as well as the seeds present in the $\mathcal{F}_{unif}$ frontier. 1,848 random seeds were inserted in the $\mathcal{F}_0$ and $\mathcal{F}_{unif}$ initial populations to control for any effect of population size. All algorithms created a temporary population of 16 individuals per generation, used a single point crossover with 1.0 probability, and a mutation rate of 0.003 was applied (with $16,891 \times 0.003 = 51$ expected random changes in every individual).

## 2.6 Results

### 2.6.1 Epistasis: Evaluation of wBCR Using the Simulation Model

The evaluation of wBCR demonstrates the effect of epistasis in the sediment model, in the sense that "the whole is not the sum of its parts" ($S(\boldsymbol{X}) \neq S_0 - \sum_{k=1}^{K} b_k x_k$). Simply adding the separate abatement benefits of each part reaches the result that the total sediment reduction surpasses the sediment baseline. Figure 2.2 (a) shows all the non-dominated solutions from scenario of $\lambda = 1$, i.e. only considering the cost and sediment in the objective space, where the epistasis is depicted by the overestimation of sediment reduction by the linearized version of the model ($S(\boldsymbol{X}) > S_0 - \sum_{k=1}^{K} b_k x_k$). Thus, there exists an attenuation of sediment reduction benefits as more effort is devoted to sediment reduction (a common finding in sediment reduction applications, as shown in Ran et al. (2013)).

Similarly, we compared the wBCR solutions based on linearization of sediment and duck benefits with the same wBCR-generated solutions evaluated via the MOSM and duck production models for the entire range of sediment objective weights ($\lambda = 0$ to $\lambda = 1$). Since the duck production model is not epistatic, the results are identical for the $\lambda = 0$ case. However, as the weight placed on sediment increases, the divergence between the two frontiers grows (see Figure 2.2(a)[5]). Since adding individual sediment reduction benefits overestimates the model-estimated benefit, at a certain point linearized benefit even surpasses the baseline, resulting in unreasonable (negative) values of outlet sediment (baseline less estimated sediment reduction).

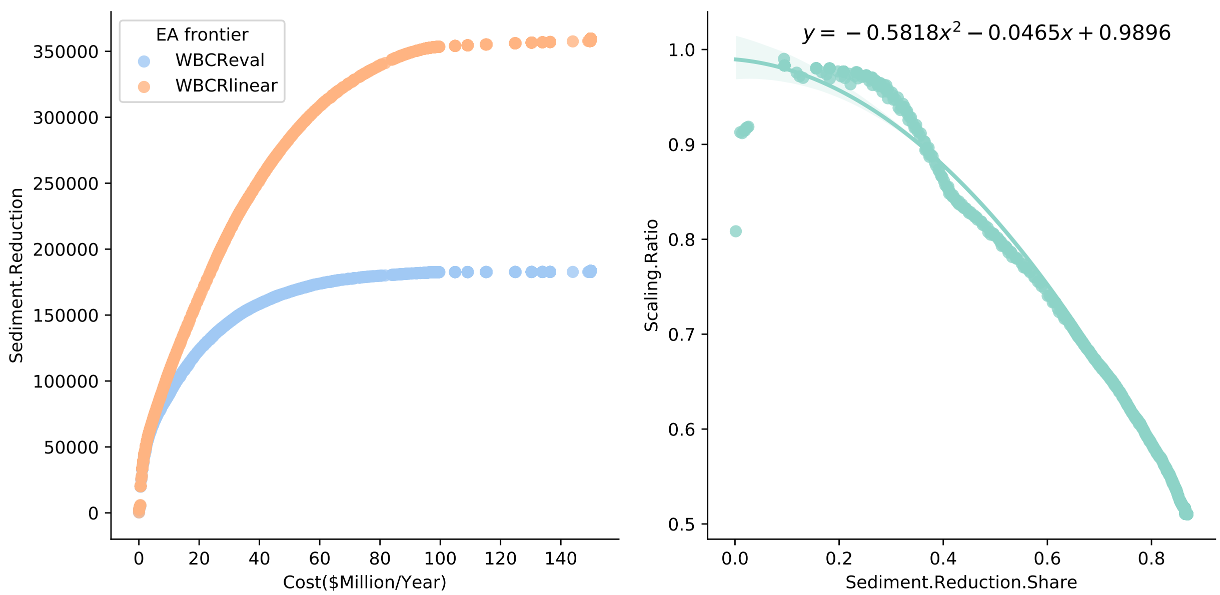


Figure 2.2: (a).Over-estimation of sediment reduction benefit by the linearized sediment reduction function. (b).Estimated extent of the scaling (attenuation) coefficient needed to adjust the linearized sediment reduction function downward to match MOSM calculations.

One can further quantify the extent of epistasis present by finding, for a particular level

[5]Visualization in https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/HIBNRC (3d-lambdaBCR.html).

of $\lambda$ and cost, a scaling coefficient $\mu(C, \lambda)$ which would result in

$$S(\boldsymbol{X}) = S_0 - \mu(C, \lambda) \sum_{k=1}^{K} b_k x_k \tag{2.4}$$

For example, for the case of $\lambda = 1$ we plot such scaling ratios as a function of desired sediment reductions (and the associated cost) in Figure 2.2(b). The scaling ratio generally decreases with desired sediment abatement, although the empirical pattern is not monotone. Based on the differences between the two wBCR frontiers in our case, it is possible to "correct" for the epistasis in the linearized wBCR by scaling down the individual sediment reduction coefficients before doing the linear summation. We do point out that the epistasis adjustment depends on the specific level of desired sediment reduction, and a generally decreasing pattern in the adjustment factor is intuitive: at very low sediment reduction levels, efficient management options affecting water storage can be found in hydrologically independent locations and no adjustment is necessary; yet as desired sediment reductions grow, selecting more management options in connected flowpaths becomes necessary, and accumulated redundancy in terms of water storage manifests itself in larger attenuation (smaller scaling coefficient). For example, for the 20% sediment reduction, the effects of epistasis seem trivial, so the adjustment will also be insignificant (scaling ratio $\approx 1$). However, for the 50% sediment reduction, we should consider multiplying the sediment coefficients by a 0.8 scaling ratio to correct for the benefit overestimation caused by epistasis. In practice, one could develop approximate scaling ratios as functions of desired abatement levels and the appropriate weights given to different objectives (a sample quadratic epistasis adjustment function for $\lambda = 1$ is shown in Figure 2.2(b). Such adjustments can be used in the development of effective (although second-best) incentive policies such as taxes, subsidies, or trading schemes which would not overestimate an individual action's contribution to pollution reduction at the watershed outlet. Note that the scaling relationship is distinct from the often discussed "delivery ratio", as linearized incremental benefit estimates already implicitly incorporate such "delivery ratios" by evaluating sediment at the watershed outlet.

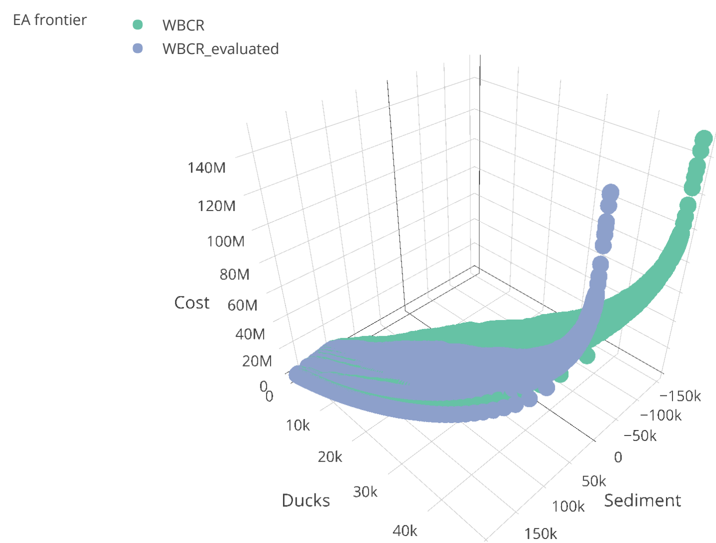


Figure 2.3: Pareto-front estimated using the wBCR method, with objectives evaluated via linear approximation (Green) versus objectives evaluated using simulation models (Blue).

### *2.6.2 Estimated Frontiers*

*Poor Performance of Unseeded EA*

Figure 2.4 presents the projections of the estimated Pareto-fronts in sediment-cost and duck increase-cost spaces. The first thing we note is that the estimated Pareto front discovered by the EA in a completely unguided fashion, $\mathcal{F}_0$, is quite inefficient. Although it manages to converge, in part, to the $\mathcal{F}_{unif}$ front at its lower envelope in sediment-cost space (Figure 2.4, purple front approaching the lower envelope of $\mathcal{F}_{unif}$ at around 50,000 tons of sediment level), it fails to do so in the duck increase-cost space by a fairly dramatic fashion, where the projections of the two fronts do not even overlap. Furthermore, the unseeded approach fails to provide good coverage of the objective space. We can be fairly confident in not recommending running EA heuristics on a realistic problem without incorporating any domain-specific knowledge about the nature of tradeoffs.

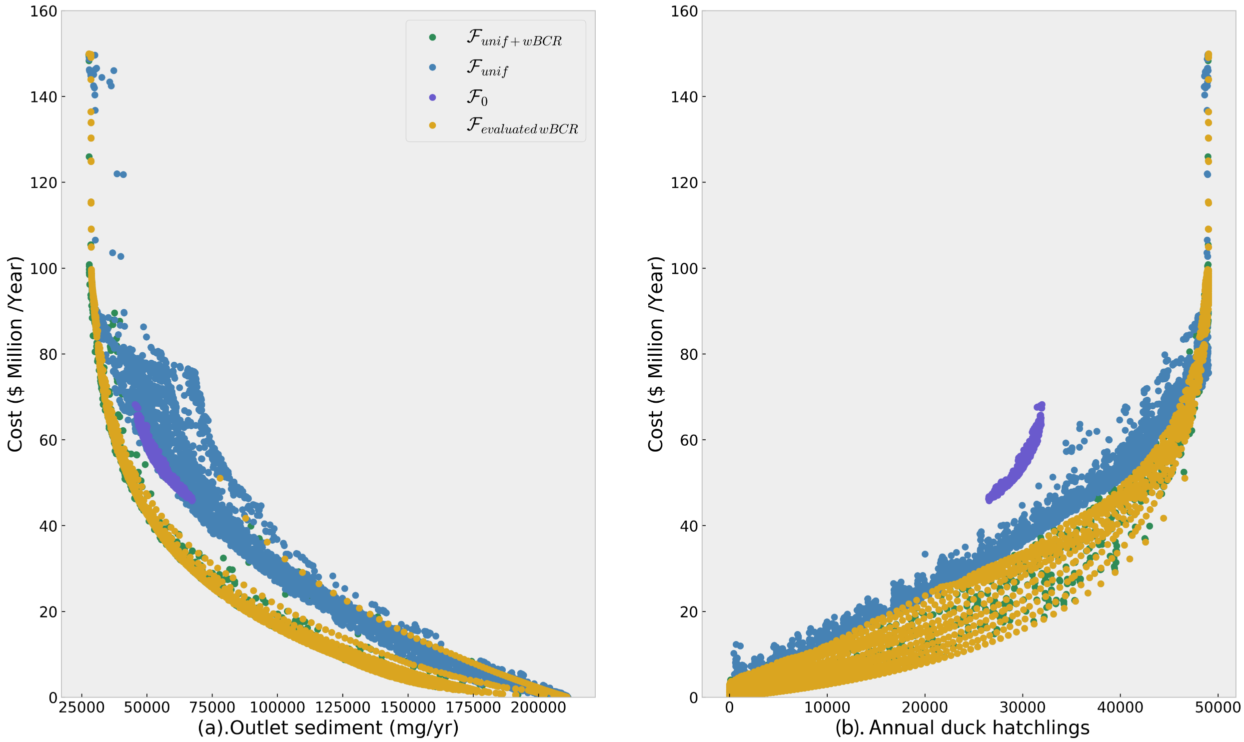


Figure 2.4: Estimated Pareto-fronts from EA with different seeding mechanisms and from evaluated wBCR solutions. (a) shows the trade-offs between sediment and cost, and (b) shows the trade-offs between duck hatchlings and costs.

Although the presence of epistasis led the linearized wBCR to overestimate sediment reduction in the objective space, 90% of the wBCR solutions are still non-dominated after the challenge by the EA. This means that in our example, the Pareto-efficiency of wBCR approaches (in terms of its ability to find the solutions in the decision space) has largely been maintained in the presence of epistasis. Sediment abatement is concave in effort, suggesting that adoption of MO attenuates the sediment reduction benefit at other MOs as compared to the incremental benefit estimated in isolation. However, this attenuation does not appear to drive individual MO's sediment reduction to zero, as that could cause the EA to exploit such effects and eliminate wBCR-based solutions from the Pareto-front. Thus, the wBCR approach, efficient under incorrect assumptions regarding the sediment objective function, is mostly efficient under the simulation approach as well.

*Benefits of Seeding*

First, we see that the seeding approach we relied upon previously (e.g., (Rabotyagov et al., 2010b)) clearly outperforms the unseeded EA results with ($\boldsymbol{\mathcal{F}}_{unif}$ clearly more efficient than $\boldsymbol{\mathcal{F}}_0$). However, given the very large search space in our applied problem, we can improve upon $\boldsymbol{\mathcal{F}}_{unif}$ by incorporating solutions obtained using the wBCR approach. In fact, seeding the EA simulation model with wBCR-derived solutions does improve the performance of EA in our application. Compared $\boldsymbol{\mathcal{F}}_{unif+wBCR}$ with $\boldsymbol{\mathcal{F}}_{unif}$, $\boldsymbol{\mathcal{F}}_{unif+wBCR}$ generated solutions that dominate the ones from $\boldsymbol{\mathcal{F}}_{unif}$, supporting our hypothesis that adding our 1848 wBCR seeds would significantly improve EA performance in both the sediment-cost and duck-cost dimensions. Efficiency gains are not trivial: for example, at the 100,000 tons/year sediment loading level (roughly a 53% reduction in sediment), $\boldsymbol{\mathcal{F}}_{unif+wBCR}$ contains solutions attaining that level at about the cost of $15 million annually, while the $\boldsymbol{\mathcal{F}}_{unif}$ frontier dictates expenditures of upward of $27 million (a 45% inefficiency). Similarly, in the duck-cost space, obtaining 30,000 hatchlings [6] is estimated to cost $16 million in the $\boldsymbol{\mathcal{F}}_{unif+wBCR}$ frontier, with roughly double that cost found in the $\boldsymbol{\mathcal{F}}_{unif}$ front. Compared to a limited seeding approach, the magnitudes of efficiency gains from using wBCR-derived seeds are large. Not surprisingly, the gains are largest in the middle of the objective space, as $\boldsymbol{\mathcal{F}}_{unif}$ "pins down" the end-points of the Pareto-front by using the zero cost baseline and the "everything, everywhere" scenario.

Even though the wBCR method does not necessarily result in Pareto-efficient solutions, we find that using the method to initialize the EA search improves EA performance substan-

[6] Our duck hatchlings were estimated from a simplified duck hatchling model, but the estimates were pretty close in line with the state duck conservation goal. If we apply a general survival rate 0.6 to the 30,000 hatchlings estimate, the duck population number is around 18,000. For Le Sueur River Basin which has the area around 2,880 $km^2$, the duck density is then around 6.25 ducks/$km^2$. According to the Minnesota State duck population survey (Minnesota DNR, 2019), the current duck population is around 3 ducks/$km^2$. Adding the increased ducks to the current population result in a density of 9 ducks/$km^2$. We assume the duck density value satisfies the constraint of carrying capacity.

tially, and that the method produces solutions, 90% of which survive the EA challenge. The practitioners of EA-inspired simulation-optimization may wish to generate scenarios based on wBCR or similar methods appropriate to their problem and test their efficiency in the EA framework. Running EAs already requires that the researchers do the (often substantial) work of being able to iteratively run the relevant simulation models, so the marginal cost of testing wBCR seeds (in addition to other scenarios which may be conjectured to perform well) is likely to be small. The benefits are two-fold. If the problem is similar to the one we analyze here, large efficiency gains are possible compared to unseeded EA approaches. Even if wBCR solutions do not perform well, the researcher will have more confidence in interpreting and communicating EA results knowing that those results have been compared to the wBCR approach directly. In fact, in our application, upon completion of the analysis, one can argue that the use of an EA for optimization is largely redundant, as a Pareto-front of reasonable quality could be obtained by 1) running the model in a one-at-a time fashion to obtain incremental benefit estimates for each decision making unit; 2) constructing the wBCR and sorting the decision making units in a descending fashion; 3) running the model for the solutions obtained via the sorting procedure to produce the tradeoff frontier in objectives space. This finding is not expected to hold in general for all environmental (and water quality in particular) models. However, we believe that several features of the model employed in this application contributed to such finding. First, by design, the wildlife objective in the model is non-epistatic, and wBCR procedure can find efficient solutions along this dimension ($\lambda = 0$) exactly. Second, for sediment-reducing options which did not involve hydrologic routing, interaction (epistasis) effects were abstracted away at the stage of MOSM model design. Finally, individual management options involving water storage (and thus expected to exhibit epistatic effects) are small compared to the overall scale of the watershed, and a selection of a single particular wetland, while decreasing the incremental effectiveness of other candidate wetlands, did not do so in a manner a) strong enough to reduce the incremental effectiveness of another wetland to 0 and/or b) disparately enough across candidate wetlands to be able to reverse the wBCR rank order. Thus, we conjecture that for models which exhibit similar characteristics, linearizing the model for purposes of optimization may be acceptable (although the performance of the solutions should still be simulated using the original process model), while applications involving decision-making units which are both expected to be interdependent and individually significant in terms of overall objectives may benefit from wBCR procedure as a seeding paradigm yet may require additional computational effort in exploiting epistatic effects in simulation-optimization.

*Selected Efficient Solutions*

As we mentioned above, 90% of the wBCR solutions survived after the EA iterations and became members of the $\boldsymbol{\mathcal{F}}_{unif+wBCR}$ frontier. We take a closer look at those common solutions of wBCR and EA with wBCR and uniform seeding. The weight $\lambda$ represents the relative importance of duck hatchlings increase over sediment reductions in the weighted benefit-to-cost ranking. Thus, a convenient consequence of most wBCR solutions surviving in the best estimated Pareto-front is that solutions can be directly interpreted in light of the weight given to the environmental benefit objectives. When $\lambda = 1$, sediment reduction is the only priority, while $\lambda = 0$ means that we only care about increasing the ducks. At the same time, this means that at a roughly same level of cost, by choosing different $\lambda$, the solutions demonstrate the presence of tradeoffs or synergies in the benefit dimension. For example, if we focus on the solutions at the level of the cost associated with a 30% sediment reduction at a $\lambda = 1$, then such exclusive focus on sediment has a "co-benefit" of 587 ducks produced. However, at a similar cost level, the "co-benefit" of duck production goes up to 3,681 hatchlings for the solutions obtained using an equal weight on 1 ton of sediment decrease or a 1 duck hatchling increase ($\lambda = 0.5$). At the same time, one sacrifices only 1 percentage point in terms of sediment reduction (solution #1800050 obtaining a 29% sediment reduction versus solution #1100100 leading to a 30% sediment reduction). Focusing on ducks at the intermediate level ($4 million per year cost) can deliver less than a third of potential sediment reductions (9% sediment reduction). At the significantly higher cost level of over $26 million (associated with a Le Sueur Watershed Council goal of a 65% sediment reduction), the tradeoffs are much less pronounced as the intensity of MO adoption leads to a greater extent of co-benefits (synergies in environmental benefits).

Table 2.5: Selected solutions from the estimated Pareto-frontier

| | **Solution ID #** | **Sediment Reduction** | **Duck Increase** | **Cost, $/year** |
|---|---|---|---|---|
| **At the cost level of 10% sediment reduction** | | | | |
| $\lambda = 1$ | 100100 | 10% | 0 | 573,057.62 |
| $\lambda = 0.5$ | 100050 | 10% | 0 | 573,057.62 |
| $\lambda = 0$ | 800000 | 1% | 2,322 | 549,465.35 |
| **At the cost level of 30% sediment reduction** | | | | |
| $\lambda = 1$ | 1100100 | 30% | 587 | 4,096,251.40 |
| $\lambda = 0.5$ | 1800050 | 29% | 3,681 | 4,043,706.90 |
| $\lambda = 0$ | 3600000 | 9% | 12,526 | 4,069,299.40 |
| **At the cost level of 65% sediment reduction** | | | | |
| $\lambda = 1$ | 5900100 | 66% | 23,386 | 26,598,914.96 |
| $\lambda = 0.5$ | 7200050 | 65% | 29,110 | 26,831,805.06 |
| $\lambda = 0$ | 7200000 | 45% | 37,999 | 26,452,110.12 |

These features of the solutions in the Pareto-frontier emerge as a result of the structure of MO evaluated. WCMO is the only assumed MO which directly benefits the duck production, so when $\lambda = 0$, the efficient solutions only choose WCMOs. 10%, 45% and 90% of WCMO are chosen respectively with the similar costs level for 10%, 30% and 65% sediment reduction. The proportions of WCMO are 0%, 2%, 50% for $\lambda = 1$, and 0%, 15%, 70% for $\lambda = 0.5$, which indicates that WCMO become a less cost-efficient option as we put more weight on sediment reduction. Instead, RAMO (ravine stabilization) has a 25%, 92%, 97% rate of selection at $\lambda = 1$ and 25%, 92%, 97% at $\lambda = 0.5$, which implies its relatively high cost-efficiency for sediment reduction. Meanwhile, the grass buffer option BFMO also plays a relatively important role in sediment reduction since it has a 5%, 30%, 40% rates of selection for both $\lambda = 1$ and $\lambda = 0.5$.

Figure 2.5 and 2.6 show the distributions and spatial patterns of MOs selected for three different cost levels and weights placed on sediment and duck objectives. Taken together, they indicate several interesting features of MO selection in the study watershed. First, ICMO (in-channel management) is never efficient to select (due to its high estimated cost and limited effectiveness in storing water). Second, RAMOs are highly cost-effective for sediment control, and almost all candidate sites are selected even for moderate (30%) sediment reduction targets. At the same time, wetland (WCMO) restoration is *not* a cost-efficient option when the focus is exclusively on sediment, and moderate sediment reductions can be attained largely without any reliance on WCMOs. Third, WCMOs become necessary for the attainment of the stated watershed goal of 65% sediment reduction, with roughly half of the WCMO candidate locations restored, which leads to significant co-benefits in duck production (over 60% of maximum attainable hatchlings at that cost level). Yet, for the cost of attaining a 65% sediment reduction goal, virtually all of restorable wetland sites could be converted, with large benefits for duck populations (yielding a concomitant 45% sediment reduction). Finally, the State of Minnesota recently adopted a regulatory policy of requiring riparian buffers (akin to BFMO in our paper). We find that 100% adoption of BFMOs is not an efficient strategy, yet when sediment reduction is the goal, selecting a sizeable portion of candidate BFMO sites is cost-efficient.

Each individual map in Figure 2.6 can be viewed as showing the least-cost locations and combinations of conservation actions for a certain scenario in terms of sediment reduction and duck hatchling increment. The results show expected spatial patterns in terms of sediment-reducing actions concentrating near the watershed outlet and the river network, and the pattern is fairly robust with respect to relaxing the assumptions about the individual benefit and cost estimates (Appendix A.7). We did not attempt to collapse the objective function into a single monetized metric, which would require models simulating the impact of a particular landscape configuration on all the relevant ecosystem services coupled with a model estimating the full economic value of the resultant pattern of ecosystem service provision. Still, a crude incorporation of existing value estimates for sediment reduction in the broader

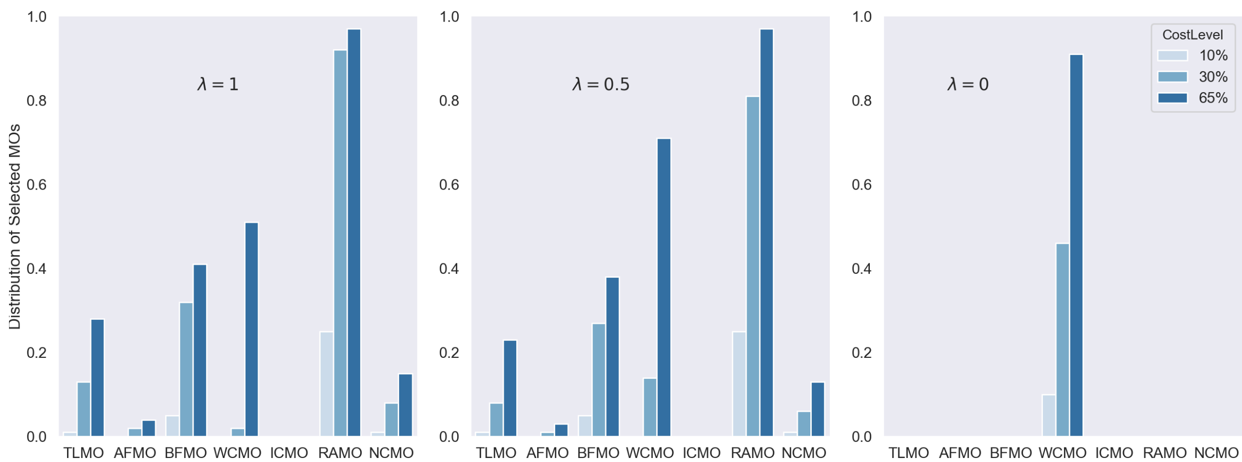


Figure 2.5: Proportion of selected MOs for the management scenarios listed in Table 2.5. Weight $\lambda$ indicates the relative importance of duck hatchlings increase over sediment reductions, and cost level can be viewed as the budget level.

study region as well as monetized value of ducks could be of interest. For example Hansen et al. (2015) assessed multiple studies of the economic value associated with duck hunting and used a value of \$106 (in 2015 dollars) per bagged duck in their estimates of monetary value of wetlands. To transfer the wetland's ecosystem service of duck hatchlings improvement to the economic values for duck hunting, they first applied a harvest rate of 5 percent (varying by the duck species) to obtained the estimation of bagged ducks from hatchlings, and then multiplied it by the amenity value of \$106 per bagged duck to estimate the total duck-hunting benefits. In our context, then, the expected value of an additional duck is approximately \$5.00, or \$2.50 (assuming a survival rate of 0.5) for each additional hatchling. So a total of 30,000 hatchlings, for instance, would result in around \$0.75 million in hunting value benefits, reducing our minimum cost value of approximatley 25 million by 3%. Similarly, for sediment reduction, Parveza et al. (2016) estimated the average monetary value of sediment reduction of \$2.32 per ton expressed in constant (year 2000) dollars. Applying a 5% inflation rate, the 2018 inflation-adjusted value will be around \$5.56 per ton. As a consequence, a 50% sediment reduction can generate about \$0.6 million in benefits, for a cumulative

5.5% in cost reduction. Clearly, such a grossly simplified valuation approach misses many other ecosystem services being generated from identified landscape patterns (e.g., nitrogen or phosphorus reductions, flood control benefits) yet it highlights the need for both the incorporation of more comprehensive models of ecosystem services and valuation approaches in future work.

As in many similar studies, (approximately) cost-efficient patterns of watershed conservation actions have been identified, including the notional water quality objectives identified locally (a 65% sediment reduction in our application). At least three challenges loom in the policy realm: identifying or refining, in light of findings, the specific environmental targets desired by or acceptable to the local stakeholders and decision-makers; finding financial resources to support voluntary conservation actions among private landowners; and implementing a targeted policy capable of approximating efficient watershed solutions. At the very least, we find that by using a simple wBCR ranking scheme, we can improve the circumstances surrounding those challenging decisions.

## *2.7 Conclusions and Future Directions*

Simulation models are important in assessing the effectiveness and efficiency of landscape conservation actions, and will likely grow in importance and relevance to environmental economics and the conservation community. Models shift the "nonpoint source" pollution problem to a more manageable problem by helping to identify both the sources of pollution and the actions for pollution abatement. Despite the legitimate concerns associated with over-parameterization and fundamental epistemic uncertainty in water quality and ecological models (see, e.g., Beven (2006)), models are indispensable in nonpoint source pollution research and policy proposals (see, e.g., Brown et al. (2015) in the context of water resources). In our application, we used a custom-built sediment model highly specific to the study watershed, but more generalizable modeling tools can provide the simulation component in simulation-optimization work and have been used elsewhere.

Once a simulation and scenario evaluation framework has been built, allowing assessment

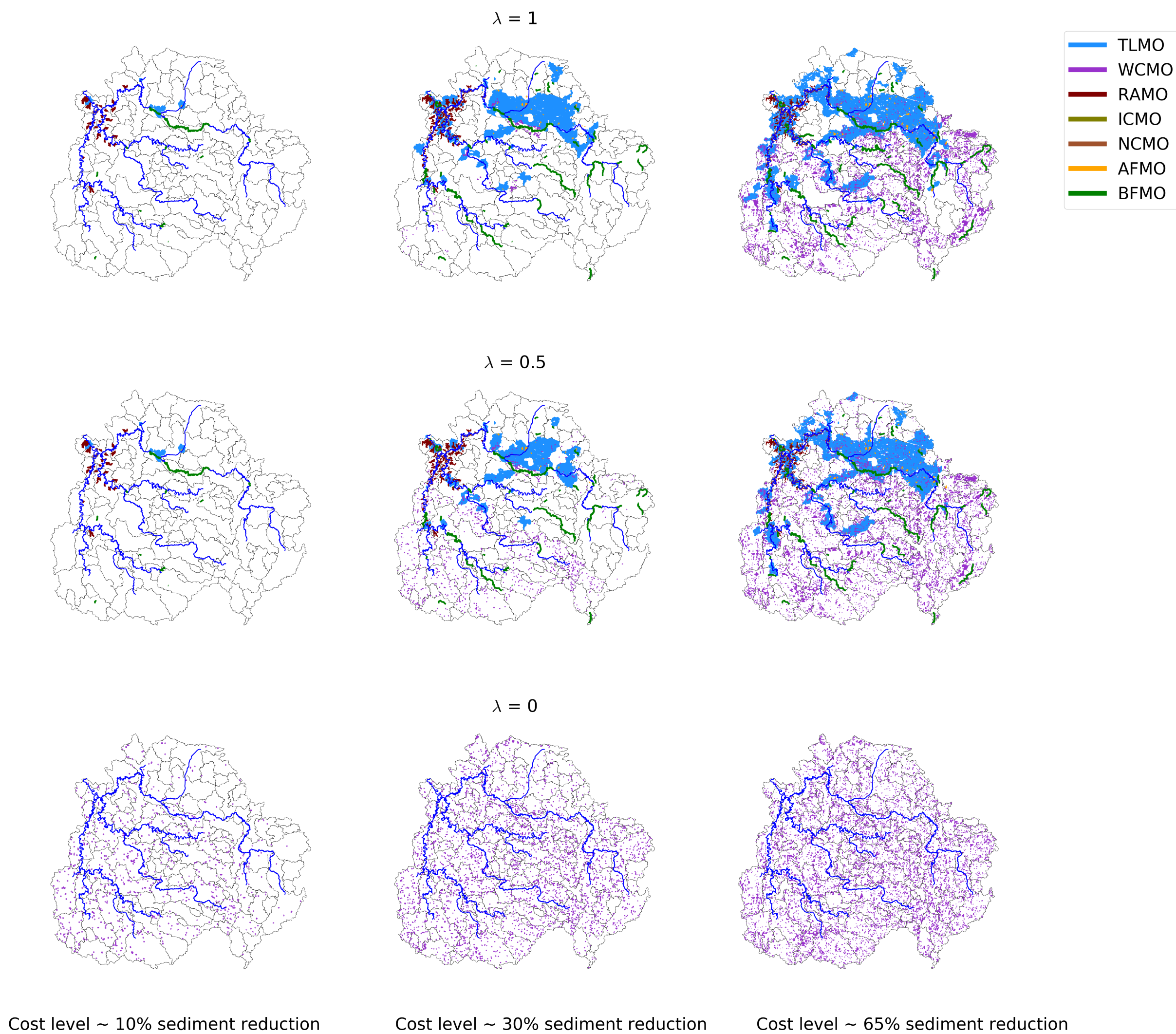


Figure 2.6: Spatial visualization of the cost-efficient conservation portfolios: the least-cost locations and combinations of conservation actions for management scenarios listed in Table 2.5. Each row represent a scenario defined by the weight ($\lambda$), indicating the relative importance of duck hatchlings increase over sediment reductions. Each column represents a scenario defined by budget (cost) level.

of scenarios of interest and setting the stage for optimization and tradeoff analysis, care needs to be exercised in using EA heuristics. Many realistic applications ask for evaluation of problems with a very large search space. Adopting an EA heuristic can help in dealing with such issues but, similar to other research, we have shown that MOEAs can get bogged down and produce tradeoff results that are not efficient. In our application, if we do not incorporate any domain-specific knowledge in terms of seeding, the algorithm produces results with a plausible shape for a Pareto-frontier yet those results are grossly inefficient. Incorporating more knowledge in the form of seeds brings successive improvements in performance. Some have referred to producing seeds as using an "intelligent paradigm" (Truemper, 2016). We show that using more sophisticated versions of the intelligent paradigm (going from several seeds, which include likely end points of the Pareto front to utilizing weighted benefit-to-cost ratio ranking) produce marked improvements in efficiency.

In our context, the relatively familiar "intelligent paradigm" of using (weighted) benefit-to-cost ratios in large part produces solutions on the estimated Pareto frontier, with the EA using this information to 'fill out' the Pareto frontier. Only 10% of wBCR solutions were subsequently dominated by the solutions found by EA. We cannot expect this to be a fully general phenomenon. That is, we expect that there will be instances where producing seeds based on a linearized approximation of the simulation model will prove to be fruitful in terms of improving efficiency, yet those solutions themselves may not survive to be members of the final estimated Pareto frontier. Even if the latter proves to be the case, results produced by EAs can sometimes be counterintuitive and difficult to interpret, both in terms of procedure used to generate the results and in rationalizing the results in a manner consistent with researchers' and stakeholders' a priori expectations on what conservation actions should be chosen and where they should be implemented. At the same time, benefit-cost rules, often described in terms such "benefit per dollar", "bang for the buck", or "return on conservation investment" are fairly well known even outside the research community, and are regularly used in describing efficient allocation of limited conservation budgets to various stakeholders. Even taken in isolation of any optimization considerations, this suggests that it may be useful to generate solutions based on benefit-cost rules and to evaluate and challenge them in a simulation framework. In the current application, most of these "greedy" solutions survive the challenge and solutions can be described directly in terms of the (weighted) benefit-to-cost ratio ranking procedure and the associated weights placed on different environmental objectives. In general, it may be the case that epistasis in the biophysical model is exploitable by the algorithm and "greedy" solutions get supplanted by solutions generated by an EA. Under those circumstances, the researchers and stakeholders can still be confident that a reasonable solution procedure has been tested and that EA solutions may inherit useful characteristics from the well-known ranking procedure.

In short, our findings suggest that an often useful precursor to undertaking an optimization heuristic such as an EA is to construct solutions, which employ the (weighted) benefit-to-cost greedy ranking procedure. Then using these solutions a) assess their performance using the simulation model employed, and b) pass these solutions to the optimization heuristic as a way to both challenge the "conventional wisdom" embedded in benefit-to-cost ranking and to provide the optimization heuristic with a set of intelligently selected starting points.

Environmental economists have long recognized that epistasis can be important, both on the environmental benefits side (e.g., Khanna et al. (2003); Parkhurst and Shogren (2007); Costello and Polasky (2004)), as well as on the cost side, typically related to the actions of self-interested entities that can produce environmental benefits (e.g., firms or individual land owners). Schroder et al. (2018) deal with epistasis on the cost side in the context of watershed optimization induced by landowners owning multiple restorable wetland locations. Clearly, methods that utilize game theory, where one agent's payoff is dependent on the actions of other agents, tackle epistasis directly (as in Fanokoa et al. (2011); Bulte and Horan (2003)). At the same time, in the nonpoint source water pollution context, complexities of ecohydrology appear to be sometimes used as a justification against implementing incentive-based policies. Kling (2011b) called for practical policies, which can be both defensible with respect to biophysical understanding of watersheds and can transparently provide trading incentives to landowners, and Rabotyagov et al. (2014a) explored this idea further and presented an empirical example (for a very skeptical look on perspectives of water quality trading, see Hoag et al. (2017)). Our current work recognizes complexities which are present on the biophysical side, yet we also find that, even when issues such as epistasis are present, reasonable simplifications can work well for a range of water quality improvement targets (and reasonable adjustments can be made to account for the main effects of epistasis). Simplifications, which linearize the problem and produce individual-level (as opposed to system-level) environmental benefits, can be useful for both optimization and tradeoff analysis, and continue to provide a basis and a rationale for a closer look at effective and approximately efficient incentive-based policies in nonpoint-source pollution problems.

# Chapter 3

# SOCIO-PSYCHOLOGICAL FACTORS THAT INFLUENCE THE ADOPTION OF CONSERVATION PRACTICES IN MINNESOTA RIVER BASIN

## *3.1 Abstract*

In the upper Midwestern United States, one of the central goals of land use and management policy is to reduce environmental and water quality degradation resulting from agricultural production without sacrificing production. The primary means available to policymakers to accomplish this is to offer incentives to farmers willing to voluntarily adopt more conservation-minded practices, often known as Best Management Practices (BMP). Although these practices provide a range of public benefits concurrently with food provision, their adoption rates have remained low, suggesting constraints in the process. We surveyed 2000 agricultural landowners in the Minnesota River Basin to collect the data for factor analysis. Under the framework Theory of Planned Behavior (TPB) and Diffusion of Innovation (DoI), we explored the underlying socio-psychological drivers of the adoption decisions for specific BMP such as wetland, cover crops, and nutrient management. We found that attitude (both favorable and unfavorable), awareness of environmental problems, and appreciation of ecosystem services significantly affected landowners' adoption intentions for the three BMP. Besides, we applied cluster analysis and identified three landowner segments: environmentally-conscious landowners, engaging-absentee landowners, and adoption-averse landowners. We provided nuanced comparisons in terms of both the socio-psychological and socio-demographic features among the landowner clusters. Our study is useful in developing targeted conservation policies for various landowner types to motivate the adoption of BMP.

### *3.2 Introduction*

Runoff from agricultural land across the Minnesota River Basin is a significant source of water pollution for both local waterways and the Gulf of Mexico (Napier, 2009). In the 2020 Minnesota's Impaired Waters List (draft) created by the Minnesota Pollution Control Agency (MPCA), 3125 surface water reaches across the state are listed as impaired, among which more than one third reaches were imparied from nutrient (746) or sediment (410) pollutant (Anderson et al., 2019). Meanwhile, the Minnesota River has been identified as a substantial contributor of excess nitrate to the Mississippi River and the Gulf of Mexico. The negative impacts on water quality from agriculture are caused by both direct losses of nutrients and sediment from fields, and indirect effects, via alterations to streamflow and channel networks (Blann et al., 2009; Vitousek and Farrington, 1997).

Best management practices, such as wetland restoration, cover crop plantation, and nutrient management work to intercept overland and surface hydrologic flow to prevent or reduce the amount of pollution generated by agricultural nonpoint sources to a level compatible with water quality goals. Over the past decades, billions of dollars have been spent to promote and incentivize the adoption of BMP (Kling, 2011a; Napier, 2009; Keiser et al., 2019). Numerous studies showcase the effectiveness of these strategies (Shortle and Horan, 2002; Dowd et al., 2008); however their ability to mitigate pollution is limited by a lack of sufficient adoption (Kamal et al., 2015), and changing conditions on the landscape (Cochard et al., 2005; Olmstead, 2010). In the United States, over 60% of land in farms are privately-owned (Vincent et al., 2017; USDA, 2018). To effectively address the gap between BMP promotion and adoption, it is vital to understand the factors that influence landowners' adoption of BMP and develop targeted incentive policies to increase the effectiveness of the BMP in water quality amelioration.

The existing social science studies about the BMP adoption are usually from two perspectives. The first type of research is based on the random utility framework. These studies focus on using econometrics models to explain how the attributes of BMP programs and the observable socioeconomic characteristics influence landowners's decisions. Such observable characteristics are usually from demographic data such as age, gender, farm size, income, land operations, etc (Joshi and Arano, 2009; Langpap, 2004; Golden et al., 2013; Poudyal and Hodges, 2009). The other type of study, on the other hand, applies socio-psychological methods to study the unobservable factors underlying landowners' decisions. As noted by Carlsson and Johansson-Stenman (2012), people's behavior is not motivated solely by economics/material payoffs; social and psychological factors such as self-image, fairness, subjective norms often influence human decision, and therefore, should be incorporated to structure incentives to shift behavior in desirable directions (Polasky et al., 2019). Some theoretical foundations that are pertinent to these analyses are the Theory of Planned Behavior (TPB) and Diffusion of Innovation (DoI). These studies are more interested in measuring the effects from unobservable psychological attributes such as value orientations, beliefs, attitudes, subjective norms, and perceived behavioral control(Bennett et al., 2017; Christie et al., 2017; Shackleton et al., 2019; Greiner, 2015). Prokopy et al. (2008b) reviewed 55 pieces of BMP adoption research and found positive environmental attitudes, awareness, and utilization of social networks more often positively impacted adoption rates. However, as noted by Reimer et al. (2014), farmers' BMP relevant behaviors are complex and context specific, and farmers are a highly diverse group with heterogeneity in personalities and preferences; production needs and ownership goals; environmental motives and proclivities for government conservation programs. Therefore, the assertion of identifying consistent and universal variables influencing BMP adoption appears to be uncertain, emphasizing the complexity of the social-environmental systems (Westlake, 2019). Thus, integrating multiple theories with the regional data to produce the results that are meaningful to local land management is necessary for improving the understanding about regional BMP adoption.

In recent years, there has been a rising interest in socio-psychological methods to study adoption decisions. Under the framework of the Diffusion of Innovation Theory (Rogers, 2010) and the Theory of Planned Behavior (Ajzen et al., 1991), numerous studies have explored the underlying psychological drivers of BMP adoption intentions/behaviors among agricultural landowners (Price and Leviston, 2014; Greiner, 2015). According to TPB, intentions (and behaviors) are functions of three basic psychological constructs: attitude, subjective norm, and perceived behavioral control. As defined by Ajzen (2005), 'Attitudes' refers to the individual's positive or negative evaluation of performing the particular behavior of interest; 'Subjective Norms' refers to the person's perceived social pressure from peer group, family, and society or culture to perform or not perform the behavior under consideration; and 'Perceived Behavioral Control' refers to the sense of self-efficacy or ability regarding a potential behavior. Fishbein and Ajzen (2011) further developed TPB into the Reasoned Action Approach (RAA) to emphasize the role of background factors in belief formation. The authors argued that a wide range of background factors in individual, social, and informational aspects such as perceived risk, past behavior, education, culture, knowledge, media and intervention, can influence behaviors by influencing the behavioral and normative beliefs that a person might hold. In this study, we frame these background factors as "Compatibility", following the definition in the DoI theory (Rogers, 2010). Specifically, "Compatibility" refers to the consistency of the behavioral intentions with the existing values, past experiences, and needs of potential adopters.

A substantial amount of literature seeks to explain landowners' adoption of particular conservation practices, including those focused on water and soil BMP (Laws et al., 2008; Lee, 2009; Ooi et al., 2011; Westlake, 2019). Previous reviews (Knowler and Bradshaw, 2007; Prokopy et al., 2008a) elicited some general consistent determinants of adoption, such as attitudes, environmental awareness, and farm characteristics. However, syntheses studies that controlled various contextual factors (e.g. study location or method) found there were few if any universal variables that regularly explain the adoption of conservation practices across past analyses (Prokopy et al., 2008b). In a more recent review, Liu et al. (2018) found the importance of BMP characteristics, information sources, subjective norms, and peer pressures in agricultural landowners' decision making. Meanwhile, landowners' risk aversion and environmental attitudes have been receiving greater focus than a decade ago.

More specifically, Reimer et al. (2012); Arbuckle and Roesch-McNally (2015) suggested that conservation promotional efforts should raise landowners' awareness of financial and environmental benefits and the compatibility of conservation practices with current farm operations to increase the adoption rate. Furthermore, it is essential to quantify and communicate potential risks and risk abatement strategies to farmers. Additionally, Dayer et al. (2016); Fishbein and Ajzen (2011) emphasized the role of past behavior in influencing behavioral intentions, although no determined causal relationships has been established between it and intentions (Prokopy et al., 2008a).

Despite ample studies of the drivers of BMP adoptions, a knowledge-practice gap still exists considering little research has been conducted regarding the adoption of all wetland, cover crop, and nutrient management BMP among private landowners in the Minnesota River Basin. Moreover, to our knowledge, few studies have leveraged the measurements of TPB & DoI attributes for additional landowner segmentation analysis. The objectives of this study include: 1).to identify the influence of TPB & DoI attributes (i.e., Attitudes, Subjective Norms, Perceived Behavioral Control, and Compatibility) on landowners' BMP adoption intentions; and 2).to reveal potential landowner clusters based on the heterogeneity in these socio-psychological attributes, and investigate if any significant socio-demographic differences were present among clusters.

The contribution of our paper is twofold. First, our research about landowners' socio-psychological attributes related to BMP adoptions provide suggestions for filling the gap between the policy objectives and landowners' policy preferences. This also represents an important pathway for building the factors which are necessary for improving policy support. Second, the identified influential factors of landowners' policy preferences can be added as independent variables into the models for quantitatively studying the incentive mechanism of conservation programs considering the individuals' preference heterogeneity.

## 3.3 Methods

### 3.3.1 Study Area

The study was conducted in the Minnesota River Basin within Minnesota State. The basin drains nearly 20% of areas in Minnesota and contains all or parts of 38 counties in the state (MRBDC, 2011). Within the basin, the Minnesota River has been cited as one of the most polluted rivers in the state and nation (Mulla, 1997; Brezonik et al., 1999). Around the time of European settlement in the mid-1800s, the Minnesota River Basin was dominated by tall-grass prairie and dotted with poorly drained wetlands (Marschner, 1974; Foufoula-Georgiou et al., 2015). Beginning in the late 1800s, surface ditches were dug and subsurface drainage tiles were installed to drain wetlands and uplands for agriculture. By 2007, agriculture accounted for around 90% of land-use in the basin. As of 2017, row crop agriculture still uses about 70% of the 14,000 $mi^2$ comprising the Minnesota River Basin, resulting in approximately 86% wetland loss in the study site since the European settlement. Agricultural practices largely disturbed the landscape and increased sediment loads to the river network, initially by top-soil erosion (Belmont et al., 2011a; Schottler et al., 2014). The Minnesota river now is the largest contributor of sediment into the Mississippi River, and the sediment and the nutrients it contains contribute to the growing "dead zone" in the Gulf of Mexico (Krohn, 2017). The State of Minnesota therefore has announced a 25 percent water quality improvement goal by 2025 (Minnesota Pollution Control Agency, 2017), along with existing stated commitments for phosphorus and nitrogen reductions, with public funds being made available to meet these goals.

Sediment and nutrient reduction strategies list a variety of best management practices (BMP) that can be implemented for reducing the sediment and nutrient loadings. In our study, we seek to improve the understanding of three BMP adoptions: wetland, cover crops and nutrient management. Previous studies have shown that small, shallow, fluvial wetlands are most frequently prioritized as efficient strategies to reduce both nitrate and sediment (Hansen et al., 2018; Czuba et al., 2018). Cover crops are also acknowledged as an effective means for reducing soil erosion and nutrient loss and increasing soil health (Arbuckle and Roesch-McNally, 2015; Abdalla et al., 2019). Nutrient management covers a series of practices concerned with what nutrients are used, how much is applied, when and where it is applied. By optimizing the nutrient uptake, it improves agricultural productivity while protecting the environment (VanDyke et al., 1999; Beegle et al., 2000).

### *3.3.2 Data Collection*

#### *Study Population*

Our MRB agricultural landowner survey was approved by University of Washington Human Subjects Division (IRB ID: STUDY00003970). Participants of our survey were recruited through a B2B crop grower panel, purchased through Survey Sampling Inc.TM, which is generally representative of the agricultural landowner population within the Minnesota River Basin. The survey was pre-tested with cognitive interviews (n = 4) though phone and video conferencing and with a mailed/online pilot survey (n = 100). The respondents for the pilot study and the final survey were recruited from the same survey panel; therefore, we can assume that respondents were sampled from the same population. We sampled 2000 landowners; a total of 1920 people received our final survey and 441 of them replied with usable data, resulting in an effective response rate around 23%. The response rate is considered as reasonable compared with the average response rates for B2B surveys, which ranges from 23% to 32% [1]. Our data panel was made up of predominantly more male at the age category of 50 -70, with some-college education level. The descriptions of the socio-demographic characteristics of the sample were presented in Table 3.1.

[1] According to the data from QuestionPro (2018), a professional survey company, the response rate for B2B surveys ranges from 23% to 32%. `https://www.questionpro.com/blog/good-survey-response-rate/`

Table 3.1: Descriptive statistics of socio-demographic characteristics of the survey sample

| Variable | Category | Study Sample (N = 441) | |
|---|---|---|---|
| | | n | % |
| Gender | Male | 345 | 78.23% |
| | Female | 90 | 20.41% |
| | Prefer not to say | 6 | 1.36% |
| Age | Under 30 | 2 | 0.45% |
| | 30-50 | 29 | 6.58% |
| | 50-70 | 236 | 53.51% |
| | Over 70 | 104 | 23.58% |
| Education | High school | 119 | 26.98% |
| | Some college | 133 | 30.16% |
| | B.A., B.S., or equivalent | 81 | 18.37% |
| | Graduate degree | 31 | 7.03% |
| Landarea | 1 to 100 acres | 57 | 12.93% |
| | 100 to 500 acres | 210 | 47.62% |
| | 500 to 1000 acres | 59 | 13.38% |
| | 1000 acres or more | 32 | 7.26% |
| | None | 5 | 1.13% |
| Income | 1-24,999 | 53 | 12.02% |
| | 25,000-99,999 | 81 | 18.37% |
| | 100,000 - 249,999 | 72 | 16.33% |
| | 250,000 - 499,999 | 55 | 12.47% |
| | 500,000 to 999,999 | 61 | 13.83% |
| | 1,000,000 and over | 15 | 3.40% |
| | None | 11 | 2.49% |

*Questionnaire Design*

To examine the socio-psychological attributes affecting landowners' adoption of BMP, we developed our questionnaire to assess a set of constructs according to the TPB and DoI theory. Specifically, we designed the indicators to cover the following attribute constructs: attitude, subjective norms, perceived behavioral control, compatibility, and communication. In the context of this paper, we defined attitudes as landowners' favorable or unfavorable evaluation of implementing BMP on their land. subjective norms were defined as landowners' perceptions about the responsibility for conservation to address social influences. Furthermore, we used perceived behavioral control to evaluate landowners' degree of belief that they are familiar with, and have the skills and resources to implement BMP on their property.

For compatibility, we defined it as the degree to which the BMP adoption is perceived as being consistent with landowners' existing values, past experiences, and their concerns and awareness related to environmental problems.

Although there is a substantial gap between intentions and subsequent action (Wieber et al., 2015), creating a measurement for intention is still necessary to study which attributes may affect landowners' decision making. In our survey, we designed questions "Are you open to adopting xxxx (wetland/cover crop/ nutrient management) on your land?" to collect data representing landowners' intentions. According to a general rule, we expect that landowners' intention to adopt BMP will be stronger under the following circumstances: when they evaluate the implementation of BMP as more favorable, when they perceive higher normative pressures, when they have more ability and knowledge to implement BMP (i.e. perceived behavior control), and when their awareness, concerns, values, and past experiences are more consistent with the goals of BMP adoption. The complete survey could be found in Appendix B.5.

### *3.3.3 Data Analysis*

#### *Factor Analysis*

Our collected dataset for factor analysis included two types of data. The first part was the 5-point Likert-scale data. In the survey we asked participants to choose their level of agreement or disagreement for each of the 46 statements on a 5-point scale: 1 = strongly disagree, 2 = slightly disagree, 3 = moderate, 4 = slightly agree, 5 = strongly agree. Besides the Likert-scale data, we had variables from a set of "check all that apply" questions, asking landowners daily usage of ecosystem services, past conservation experiences, opinions about environmental situations and conservation responsibilities. Since we have both the Likert-scale data and the dichotomous data, we conducted factor analysis separately for them.

The factor analysis of our study includes both an exploratory factor (EFA) analysis to explore and derive factor structures and a confirmatory factor analysis (CFA) to test and validate the measures and confirm the relationships of indicators to their respective TPB & DoI constructs. The results of factor analysis provided the predicted factor scores for each individual, which would then be applied to a logistic regression model for estimating the effects on the probability for BMP adoptions. Finally, we performed a cluster analysis to examine the underlying groups of landowners based on their socio-psychological differences.

Prior to conducting analyses, we addressed missing values using a multiple correspondence analysis (MCA) model based on prior research recommendations (Josse et al., 2016; Kassambara, 2017). To measure the internal consistency of our data, we applied Cronbach's alpha ($\alpha$) with a cutoff threshold of 0.7, which was concerned with the degree of interrelatedness among a set of indicators designed to measure a single construct (Cronbach, 1951; Netemeyer et al., 2003). For dimensionality reduction and structure exploration, we conducted EFA using the principal components factor analysis (PCA) with the VARIMAX rotation. Then, We applied the rule of thumb "eigenvalue-greater-than-one" and the scree plot to determine the number of factors to extract. The item retention for a factor is based on the criteria that the factor loadings should be no less than 0.40 but no greater than 0.90 (Netemeyer et al., 2003). We then performed a confirmatory factor analysis (CFA) to confirm our measures of the constructs, and further tested the reliability and validity of the measures. We calculated the composite reliability (CR) for each construct to determine if they met the cutoff threshold $> 0.70$, according to Hair et al. (1998), for construct reliability. The construct validity assessment was based on the average variance extracted(AVE) values, which had been advocated for a rigorous level of 0.50 or above (Fornell and Larcker, 1981).

The fitness of the CFA model was evaluated based on multiple model fit statistics, including the root-mean-square-error-of-approximation (RMSEA), the Tucker and Lewis index (TLI), and the comparative fit index (CFI), as recommended by prior research(Fornell and Larcker, 1981; Hair et al., 2011). The RMSEA represents per degree of freedom, the discrepancy of the model's approximate covariance matrix versus the observed covariance matrix. RMSEA values less than 0.05 indicate good fit; ranging from 0.08 to 0.10 indicate mediocre fit, and those greater than 0.10 indicate poor fit (Hu and Bentler, 1999; Byrne, 2016). The

TLI depicts the improvement of the model's fit relative to the null model. The CFI also examines the incremental fit compared to the null model, while taking the sample size into account. For both TLI and CFI, the acceptable level for an adequate model fit is above 0.80 (Browne and Cudeck, 1992; Pop et al., 2019), while a value of 0.90 or higher is widely considered as an indicator of good fit (Netemeyer et al., 2003; Byrne, 2016).

*Logistic Regression*

After obtaining the constructs from factor analysis, we then study the relationships between TPB & DoI constructs and intentions for BMP adoptions. The intention variables in our study are defined by landowners responses to survey questions whether or not they are open to the adoption of wetland/ cover crop / nutrient management on their land ( 1 = yes and 0 = no).

Since the response variable is dichotomous, we apply logistic regression to evaluate the effects of TPB & DoI constructs on the probability of positive intention. The logistic regression defines the probability of $P(I = 1)$ as:

$$P(I = 1) = \frac{exp(\beta_0 + \beta X)}{1 + exp(\beta_0 + \beta X)} \tag{3.1}$$

in which $X$ is the vector of the TPB & DoI constructs and $\beta$ are the coefficient parameters. Thus, the odds of $I = 1$ is then:

$$Odds(I = 1) = exp(\beta_0 + \beta X) \tag{3.2}$$

Taking the log value of both LHS and RHS, the equation becomes:

$$log(odds) = \beta_0 + \beta X + \epsilon \tag{3.3}$$

The estimated value $\beta$ represents the change in the log odds of intention (I=1) when the corresponding predictor variable increases with one unit.

*Cluster Analysis*

Meanwhile, using the constructs from factor analysis, we conducted a K-Means non-hierarchical cluster analysis for landowners classification. K-Means divides data into K clusters, and assigns each observation to one of the k clusters so as to minimize a measure of dispersion within the cluster (Shmueli et al., 2017). Here, we applied the sum of squared Euclidean distances from the cluster means as the measure of cluster dispersion, and sorted each observation into only one cluster. We explored 2-, 3-, 4-, 5- cluster solutions, choosing the one that minimizes intra-cluster distances while maximizing inter-cluster distances, and is meaningful for interpretation. We then compared the factor scores, estimated intention, and descriptive statistics of landowner demographics (including spatial heterogeneity) of each cluster to better understand the differences among the clusters.

## 3.4 Results

### 3.4.1 Estimating the TPB & DoI Constructs

For the Likert-scale data part, our data showed initial evidence of reliability for each construct (Cronbach's $\alpha > 0.70$). The EFA revealed unidimensionality for the Compatibility construct. The indicators in the Attitude construct were divided into favorable and unfavorable attitude factors. The indicators of the Subjective norm construct and Perceived behavior control construct were rearranged and grouped into favorable attitude factor and behavior control factor. Table 3.2 showed the identified latent factors and their indicators with loading values from EFA.

After removing indicators with low factor loadings ($< |0.4|$), we constructed the theoretical CFA models and fit the data. The results of our CFA models showed evidence of reliability and validity with each construct's composite reliability (CR) exceeding 0.70 and total average variance extracted (AVE) value greater than 0.50. The model fit indices were acceptable but not excellent (TLI = 0.82, CFI = 0.83, and RMSEA = 0.08).

For the "check all that apply" dataset (binary), the factor analysis was performed over the heterogeneous correlation matrix that we calculated for each pair of variables in our data. EFA reveals three dimensions under the Compatibility construct and one dimension under the subjective norms construct. See Table 3.3 for the list of indicators under each latent factors. The reliability and validity of CFA was determined based on the composite reliability (CR) for each construct greater than 0.70 and average variance extracted (AVE) greater than 0.50. And model fit was deemed moderate with a review of RMSEA (0.06), CFI (0.91), and TLI (0.90).

From the CFA models, we finally obtained the predicted factor scores for each individual in terms of all of the TPB & DoI constructs. We then applied these scores to predict intention and study landowner segmentation.

Table 3.2: Indicators with factor loadings under each latent factor (From Likert-scale dataset)

| Constructs | Indicators | Standardized Factor loadings |
|---|---|---|
| Attitude (wetland)_unfavorable | The cost of restoring wetlands is too high. | 0.71 |
| | Restoring wetlands causes loss of control over one's land, even if no easement is created. | 0.68 |
| | It is difficult to move equipment in the field with restored wetlands. | 0.67 |
| | The cost and effort of maintaining wetlands is too high. | 0.74 |
| Attitude(nm)_unfavorable | Nutrient management plan reduces crop yields in the short term. | 0.76 |
| | Nutrient management plan reduces crop yields in the long term. | 0.77 |
| | The cost for nutrient management plan is too high | 0.45 |
| | Nutrient management plan improves soil quality. | -0.47 |
| Attitude_favorable | I think soil and water conservation are important. | 0.50 |
| | I think farmers and other watershed residents should work together to protect watershed. | 0.54 |
| | I think farmers and conservation agency staff should work together to protect watershed. | 0.59 |
| | Wetlands are key to maintaining high quality wildlife habitat. | 0.42 |
| | Wetlands protect water quality by catching soil and nutrients before they flow into streams. | 0.54 |
| | Cover crops reduce soil loss from fields | 0.61 |
| | Cover crops improve soil quality. | 0.65 |
| | Cover crops lower the input of nutrients for crops. | 0.46 |
| | Nutrient management plans reduce fertilizer costs. | 0.40 |
| Compatibility_concern | How concerned are you about the current scenic quality of waterways in the Minnesota River Basin? | 0.76 |
| | How important is the achievement of moderate improvements in scenic quality to you? | 0.71 |
| | How important is the achievement of major improvements in scenic quality to you? | 0.76 |
| | How concerned are you about the current levels of nutrient pollution in Basin's waters? | 0.78 |
| | How important is the achievement of a moderate reduction in nutrient levels to you? | 0.79 |
| | How important is the achievement of a major reduction in nutrient levels to you? | 0.81 |
| | How concerned are you about the current ability of the Basin to provide high-quality habitat? | 0.84 |
| | How important is the achievement of a moderate improvement in habitat quality to you? | 0.83 |
| | How important is the achievement of a major improvement in habitat quality to you? | 0.83 |
| | How concerned are you about the current levels of sediment in Basin's waters? | 0.82 |
| | How important is the achievement of a moderate reduction in sediment levels to you? | 0.82 |
| | How important is the achievement of a major reduction in sediment levels to you? | 0.82 |
| | How concerned are you about your current ability to safely and enjoyably engage in aquatic recreation in the Basin's waters? | 0.82 |
| | How important is the achievement of a moderate improvement in the recreation potential of Basin's waters to you? | 0.84 |
| | How important is the achievement of a major improvement in the recreation potential of Basin's waters to you? | 0.84 |
| | I think water contamination is an important environmental problem in our watershed. | 0.50 |
| | I think farming practices and land use should be regulated to reduce pollution to surface water. | 0.40 |
| Behavior control | I consider myself as a steward of the land. | 0.61 |
| | I know what steps to take to conserve soil and water on my land. | 0.56 |
| | How familiar are you with the process and the costs of wetland restoration? | 0.50 |
| | How familiar are you with cover crops? | 0.54 |
| | How familiar are you with nutrient management plans? | 0.63 |
| | How familiar are you with the "25 by 25 goal"? | 0.42 |

Table 3.3: Indicators with factor loadings under each latent factor (From binary dataset)

| Constructs | Indicators | Standardized factor loadings |
|---|---|---|
| Compatibility_past experience | Crop varieties and rotation | 0.86 |
| In the past five years I applied.... | fertilizers/chemicals and cultivation practices. | 0.89 |
| | Marketing and crop insurance. | 0.87 |
| | Adoption of one-season conservation practices | 0.61 |
| | Adoption of long-term conservation practices | 0.47 |
| | Government conservation programs (CRP, EQIP, etc.) | 0.66 |
| Compatibility_appreciation | Fished in a lake, river, or creek | 0.46 |
| In the past 12 months, I.... | Swam in a lake, river, or creek | 0.62 |
| | Explored or waded along a river or creek | 0.64 |
| | Kayaked or canoed | 0.53 |
| | Hunted | 0.42 |
| | Hiked or viewed wildlife | 0.54 |
| | Used a bike trail | 0.42 |
| Compatibility_aware | High level of sediment in the river | 0.66 |
| What do you think about water-related environmental problems in the Basin | High level of nutrients in the river | 0.78 |
| | Odor from the river | 0.91 |
| | Trash in the river and along the bank | 0.62 |
| | Lack of fish or aquatic life | 0.89 |
| | Unsafe to swim or wade in the river | 0.86 |
| | Unnatural colors of the water and rocks along the river | 0.89 |
| | Unsafe drinking water from wells | 0.89 |
| Subjective norm | Landowners should be responsible for soil and water conservation in the watershed | 0.49 |
| Who do you think should be responsible for soil and water conservation in the watershed? | Farm Managers should be responsible for soil and water conservation in the watershed | 0.76 |
| | Government conservation staff should be responsible for soil and water conservation in the watershed | 0.73 |
| | Renters should be responsible for soil and water conservation in the watershed | 0.72 |
| | Minnesota River Basin Board should be responsible for soil and water conservation in the watershed | 0.71 |

### *3.4.2 Effects on Intention*

The results of logistic regression models confirm the significant effects of Attitude (both favorable and unfavorable), Awareness and Appreciation on the intentions of adoption for all of the three BMP (see Table 3.4). Consistent with the TPB & DoI theories, landowners with more favorable attitudes to BMP, being more aware of environmental problems, and more appreciating ecosystem services would be more likely to adopt BMP. On the other hand, the unfavorable attitudes towards BMP would negatively affect the intentions of adoption.

For cover crop and nutrient management, past experience has significant positive influences on the intention, while the subjective norms have negative impacts. The negative sign of social pressure is not intuitive at the first glance. However, the indicators under this construct are phrased to elicit landowners' opinions about which individuals or agencies they think are responsible for water conservation. Similar to the free-rider problem with public goods, it is possible that landowners with higher scores at this construct have the attempts to transfer their responsibility of water conservation to others, but choose not to adopt BMP by themselves.

The effects of Concern and Behavioral control constructs are not significant for all BMP based on our model results. The intercept term represents the role of other factors not included in the model. Some previous study (Wauters et al., 2010) also included the interaction terms between different TPB constructs in the logistic model. However, in our case, models with interaction terms didn't improve the model fit significantly (Likelihood ratio test p-value $> 0.1$).

Table 3.4: Coefficient estimates (standard errors) from logistic regression for intention. Note: in terms of interpreting the coefficients, negative coefficients are interpreted as having a negative impact on intention

| | Wetland | Cover Crop | Nutrient Management |
|---|---|---|---|
| Intercept | -1.14 (0.13)*** | 0.565 (0.116)*** | 0.454 (0.120)*** |
| concern | -0.20 (0.23) | -0.285 (0.209) | -0.277(0.219) |
| att_wld_neg | -1.09 (0.34)** | - | - |
| att_nm_neg | - | - | -1.224 (0.262)*** |
| att_fav | 2.06 (0.70)** | 2.672 (0.533)*** | 2.691 (0.589)*** |
| behavioral_control | 0.56 (0.50) | 0.005 (0.411) | 0.467 (0.471) |
| aware | 1.41 (0.38)*** | 2.414(0.402)*** | 1.750 (0.395)*** |
| past_experience | 0.08 (0.35) | 0.535 (0.307)* | 0.945 (0.327)** |
| appreciation | 3.26 (0.35)*** | 1.920(0.688)** | 2.323 (0.724) ** |
| social | -0.008 (0.84) | -2.992(0.840)*** | -2.746 (0.872) ** |
| Pseudo-R2 | 0.244 | 0.193 | 0.264 |

*** p-value $< 0.001$, ** p-value $< 0.05$, * p-value $< 0.1$

### *3.4.3 Landowner Segmentation*

Using K-Means cluster analysis, we segmented landowners into three distinct clusters. We named each of the clusters based on their TPB construct characteristics. Table 3.5 and Figure 3.1 show the comparisons of factor scores of the constructs among landowner clusters.

Cluster 0 contained 95 cases (22%) and was named “engaging-absentee landowners”, Cluster 1 contained 211 cases (47%) and was named “adoption-averse landowners”, Cluster 2 contained 135 cases (31%) and was named as “environmentally conscious ” landowners. Hypothesis tests indicated that the clusters are not homogeneous with regards to their intentions for BMP intentions, most of the TPB constructs, as well as demographic characteristics.

From the psychological constructs comparison, we see that the “environmentally conscious” cluster (cluster 2) appreciate more of the ecosystem services, they are more concerned and aware of environmental problems, and have more past experiences related to BMP. Their favorable attitude over the BMP is higher while the unfavorable attitude is lower. Also, the subjective norms will have more impact on them. In terms of demographic characteristics, cluster 2 have a relatively high percentage of landowners with younger age (30-50 and 50-70) and higher education level ( B.A., B.S., and Graduate degree). Detailed comparisons about the demographic characteristics among landowner clusters were presented in Table 3.6 and Table 3.7.

Landowners in cluster 0 do have high concerns about environmental problems, but they pay less attention to the ecosystem services. They are aware of the benefits about BMP according to their relatively high favorable attitudes towards BMP, but the costs about BMP may outweigh the benefits to their opinions (because they also have high unfavorable attitudes scores). They have few past experiences of BMP and are less knowledgeable about the BMP. We name this cluster as “engaging-absentee”. Regarding the demographics characteristics, landowners in this cluster have a relatively high percentage of females with older age, lower education and lower income level. Also, only 11% of them are in charge of a day to day farm operation on the land.

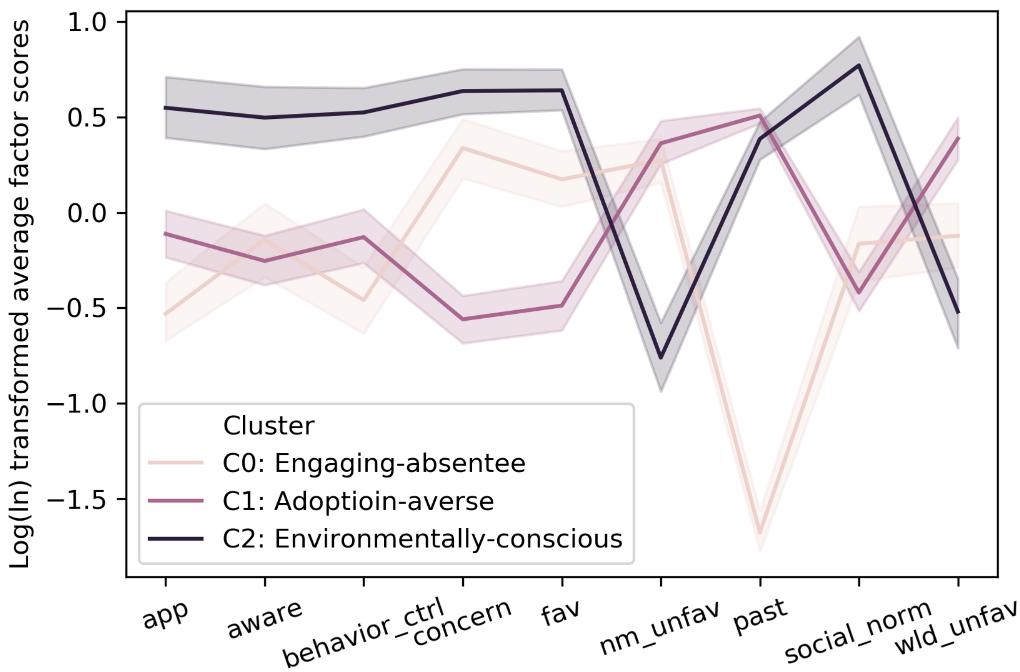


Figure 3.1: Construct deviations among landowner clusters

Table 3.5: Factor scores comparisons among landowner clusters. Note: The distributions of factor scores were not Normal distribution. Therefore, the non-parametric test Mann–Whitney U test was applied to evaluate the null hypothesis that the factor scores from different landowner clusters had the same distribution.

| Constructs | Mean Scores (SD) | | | Mann-Whitney U test. | | |
|---|---|---|---|---|---|---|
| | Cluster 0 | Cluster 1 | Cluster 2 | Cluster 0 vs. Cluster 1 | Cluster 0 vs. Cluster 2 | Cluster 1 vs Cluster 2 |
| Appreciation | -0.100 (0.134) | -0.022(0.182) | 0.105(0.199) | *** | *** | *** |
| Aware | -0.047(0.306) | -0.080(0.304) | 0.158(0.313) | - | *** | *** |
| Concern | 0.252(0.678) | -0.457(0.625) | 0.536(0.706) | *** | ** | *** |
| Past experience | -0.636(0.193) | 0.192(0.125) | 0.147(0.237) | *** | *** | ** |
| Attitude_favorable | 0.056(0.282) | -0.177(0.306) | 0.238(0.272) | *** | *** | *** |
| Attitude_unfavorable_wld | -0.085(0.456) | 0.214(0.522) | -0.275(0.498) | *** | ** | *** |
| Attitude_unfavorable_nm | 0.137(0.383) | 0.223(0.532) | -0.446(0.554) | ** | *** | *** |
| Subjective norms | -0.024(0.151) | -0.064(0.111) | 0.117(0.135) | * | *** | *** |
| Behavior control | -0.136(0.253) | -0.038(0.292) | 0.155(0.261) | ** | *** | *** |

*** p-value $< 0.001$, ** p-value $< 0.05$, * p-value $< 0.1$

Table 3.6: Demographic characteristics comparisons among clusters

| | | Cluster 0 Engaging-absentee | Cluster 1 Adoption-averse | Cluster 2 Environmentally-conscious |
|---|---|---|---|---|
| Gender | Male | 78% | 96% | 92% |
| | Female | 18% | 2% | 8% |
| | Prefer not to say | 4% | 2% | 0% |
| Age | Under 30 | 0% | 1% | 0% |
| | 30-50 | 4% | 8% | 10% |
| | 50-70 | 35% | 69% | 74% |
| | Over 70 | 62% | 22% | 16% |
| Education | High school | 50% | 37% | 18% |
| | Some college | 23% | 40% | 36% |
| | B.A., B.S., or equivalent | 14% | 18% | 34% |
| | Graduate degree | 13% | 5% | 12% |
| Landarea | 1 to 1000 acres | 24% | 11% | 17% |
| | 100 to 500 acres | 67% | 57% | 56% |
| | 500 to 1000 acres | 8% | 21% | 16% |
| | 1000 acres or more | 1% | 11% | 11% |
| Income | None | 13% | 1% | 1% |
| | 1-24,999 | 35% | 7% | 13% |
| | 25,000-99,999 | 40% | 20% | 20% |
| | 100,000 - 249,999 | 8% | 25% | 22% |
| | 250,000 - 499,999 | 4% | 18% | 18% |
| | 500,000 to 999,999 | 0% | 23% | 21% |
| | 1,000,000 and over | 0% | 6% | 5% |
| Income from farming | 0% | 16% | 1% | 3% |
| | 1-25% | 24% | 10% | 16% |
| | 25-50% | 20% | 8% | 10% |
| | 50-75% | 21% | 25% | 21% |
| | 75-100% | 19% | 56% | 50% |
| Land operation | I am in charge of a day to day farm operation | 11% | 85% | 82% |
| | someone else is in charge of a day to day farm operation | 76% | 11% | 14% |
| | majority of land is not currently used for farming | 13% | 4% | 4% |
| Region | Northeast | 1% | 1% | 0% |
| | Northwest | 6% | 1% | 3% |
| | Southeast | 3% | 1% | 1% |
| | Southcentral | 52% | 38% | 35% |
| | Southwest | 15% | 26% | 32% |
| | Westcentral | 23% | 33% | 29% |

Landowners in cluster 1 are interesting. They have a highest score in the dimension of “past experience”, indicating that they may have participated in land management programs before. However, they are at a relatively low level in other TPB dimensions such as “awareness about environmental problems” and “concern about water quality issues”. In addition, they have the least favorable attitudes but the most unfavorable attitudes towards BMP. And the subjective norms has a low impact on them. We expect landowners in this cluster to be averse to adopt BMP in the future. Although they have past experiences with the conservation program, they may think it’s not necessary to continue. Or it’s possible that they do not have a good experience with the previous incentive programs. Landowners in this cluster are mostly male (96%), with age over 50 (91%). 85% of them are in charge of a day to day farming on the land and obtain more than 75% income from farming.

Table 3.7: Chi-square test $\chi^2(\mathrm{DF}, N = n_1 + n_2)$ for cluster comparisons about demographic characteristics. Note: Null hypotheses are the distributions of the categorical data in different clusters have no differences.

| | Cluster 0 vs Cluster 1 | Cluster 0 vs Cluster 2 | Cluster 1 vs Cluster 2 |
|---|---|---|---|
| Gender | $\chi^2$(2, 306) = 22.25*** | $\chi^2$(2, 230) = 9.75** | $\chi^2$(2, 346) = 7.49** |
| Age | $\chi^2$(3, 306) = 43.73*** | $\chi^2$(3, 230) = 44.37*** | $\chi^2$(3, 346) = 168.95*** |
| Education | $\chi^2$(3, 306) = 12.44 ** | $\chi^2$(3,230) = 4.08*** | $\chi^2$(3, 346) = 19.81*** |
| Land area | $\chi^2$(4, 306) = 19.61*** | $\chi^2$(4, 230) = 13.14** | $\chi^2$(4, 346) = 3.89 |
| Income | $\chi^2$(6, 306) = 83.57*** | $\chi^2$(6, 230) = 56.7*** | $\chi^2$(6, 346) = 3.85 |
| Income from farming | $\chi^2$(4, 306) = 61.94*** | $\chi^2$(4, 230) = 29.39*** | $\chi^2$(4, 346) = 7.01 |
| Land operation | $\chi^2$(2, 306) = 149.44*** | $\chi^2$(2, 230) = 107.71*** | $\chi^2$(2, 346) = 0.88 |
| Region | $\chi^2$(6, 306) = 25.38*** | $\chi^2$(6, 230) = 18.11** | $\chi^2$(6, 346) = 8.99 |

*** p-value < 0.001, ** p-value < 0.05, * p-value < 0.1

In terms of the intention comparison, the percentages of landowners with positive intentions are significantly higher (Chi-square test p-value < 0.001) in cluster 2 for all types of BMP (55% for wetland, 75% for cover crop and 82% for nutrient management) than those in cluster 0 (26% for wetland, 55% for cover crop and 42% for nutrient management) and cluster 1 (16% for wetland, 53% for cover crop and 48% for nutrient management). The differences of the proportions of positive responses in cluster 0 and cluster 1 are not significant for cover crop and nutrient management. For wetland restoration, cluster 0 has a significantly higher positive response (Chi-square test p-value = 0.052) than cluster 1.

The similar trend could also be found when comparing the predicted intentions obtained from our logistic regression models. Figure 3.2A shows the percentage of positive responses to the BMP intention questions among the clusters, while Figure 3.2B compares the predicted probabilities of adoptions based on the regression model estimation. The probability of adoption in cluster 2 are significantly higher than cluster 0 and cluster 1 (Mann-Whitney U test p-value < 0.001). The differences between cluster 0 and cluster 1 are not significant for wetland and cover crop, while cluster 1 is significantly higher than cluster 0 in terms of nutrient management.

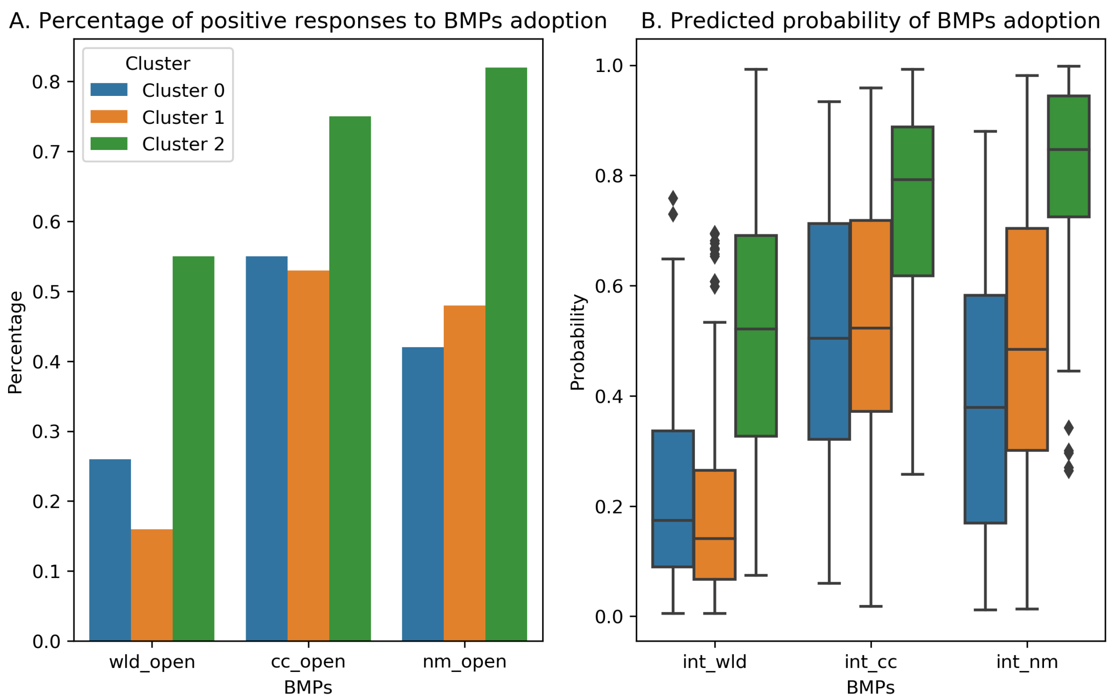


Figure 3.2: BMP adoption intention comparisons. (A) shows the percentage of positive responses to the BMP intention questions among the clusters. (B) compares the predicted probabilities of adoptions based on the regression model estimation.

We also compared the spatial heterogeneity (at the region level) among the three clusters. The majority of landowners in our sample are located in the south central, southwest and west central part of the Minnesota State. The results from chi-square test regarding the proportion of landowners in each region indicate significant differences between cluster 0 and cluster 1, cluster 0 and cluster 2. But the differences are not significant between cluster 1 and cluster 2. In Cluster 0, more than 50% of landowners are located in the south central part, while in Cluster 1 and Cluster 2 the proportions are more evenly distributed among the three regions. In cluster 1, 38%, 26%, and 33% landowners are located in the south central, southwest, and west central regions respectively. In Cluster 2, the proportions are 35%, 32%, 29%.

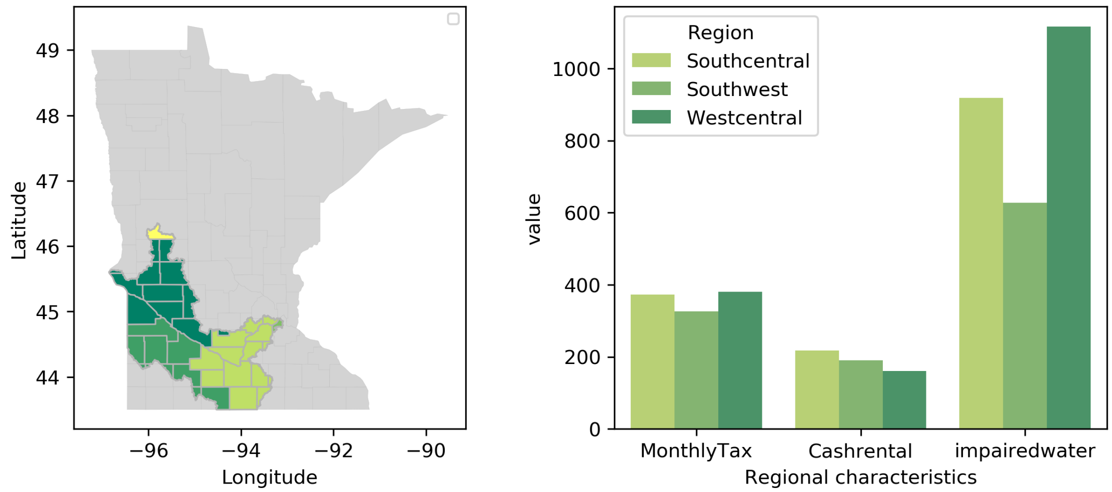


Figure 3.3: Regional characteristics comparisons among clusters. Note: the map (left) displays the locations of the three regions, and the indices (right) of monthly tax, cash rental rates and the number of impaired water bodies are selected to represent the living cost, agricultural land value, and the environmental situations in the three regions.

Although studying the regional differences is beyond the scope of this study, we do compare several indices related to the regional economics & environmental characteristics. We select the indices of monthly tax, cash rental rates and the number of impaired water bodies to represent the living cost, agricultural land value, and the environmental situations in the regions (see Figure 3.3). Southwest has the least number of impaired water bodies and the lowest monthly tax value. Meanwhile, it has a relatively higher percentage of the "environmentally conscious" landowners (Cluster 3). The cash rental rates in the south central region is higher than the other two, indicating that agriculture might be more profitable here. This is also consistent with our finding that more proportion of the engaging-absentee landowners (Cluster 0) are located in this region. In addition, the west central region has the largest number of impaired water bodies, the monthly tax is relatively high although the cash rental rate is relatively low. In the meantime, the "adoption-averse" cluster (Cluster 1) has a relatively higher proportion of landowners located in the region. Exploring the quantitative relationships between the regional characteristics and the landowners TPB constructs would be beneficial for BMP policy targeting. In reality, the psychological information about landowners might not be available for most of the environmental agencies. However, the regional economics and environmental data are usually accessible for analysis and policy design. We will leave this part for further studies.

### *3.5 Discussion*

During the recent decade, incorporating socio-psychological aspects of private landowners have become an integral part of the conservation research. Numerous studies, both theoretically and empirically, have shown that landowners' attitudes, value orientations, beliefs, subjective norms, and perceived behavioral control significantly affect their intention to BMP adoption. Our study was an empirical attempt to study Minnesota River Basin agricultural landowners' social-psychological attributes and their intentions to wetland, cover crop and nutrient management BMP adopting. In addition, we incorporated cluster analysis based on the psychological constructs to further investigate the group differences among landowners. Multiple types of landowner segmentation typologies were defined based on psychological concepts. Meanwhile, we compared the demographic distinctions among different segmentation, because in real practice the conservation agencies are more likely to be able to get access to this type of information.

In our study, we leveraged landowner survey and factor analysis to develop and validate measures of the TPB & DoI constructs, aiming to quantify those unobserved psychological characteristics, and extract the underlying drivers of landowners' BMP adoption intentions. Tests showed the measurements meet the criteria of reliability and validity, allowing for the interpretation of relationships between the indicators and TPB & DoI constructs. According to our results, the Attitude constructs were divided into "favorable attitude", "unfavorable attitude towards wetland" and "unfavorable attitude toward nutrient management". We found that these attitude factors had the strongest effects on intentions for all three BMP adoptions. And for both wetland and nutrient management, the magnitude of positive impacts from the favorable attitudes were greater than the magnitude of negative impacts from the unfavorable attitudes.

The compatibility construct in our model is composed of the factors “concerns about water quality issues”, “awareness about environmental problems”, “appreciation of ecosystem services”, and “past experience about BMP”. Our results showed that “awareness” and “appreciation” both have significantly positive impacts on behavioral intentions for all three BMP, while “concern” didn’t have significant impacts. The past experience factor only significantly affected (in a positive way) cover crop and nutrient management adopting intention. It is possible that because cover crop and nutrient management BMP are more widely applied in conservation programs like CRP, EQIP, etc than wetland restoration, so landowners’ past experiences are more related to cover crop and nutrient management instead of wetland restoration.

The Perceived behavior control construct, described by landowners familiarity to BMP, was found not significant for all three BMP adopting intentions. We suspect that the insignificance might be due to our indicator wording. Asking the familiarity to a BMP might still be too vague to extract useful information. We suggest further studies to specify the skills, techniques, and knowledge related to BMP when designing indicator wording, instead of only asking “How familiar are you with wetland restoration”, for instance.

For the BMP of cover crop and nutrient management, the significant effects of subjective norms were negative. This was beyond our expectation at first glance. However, since water conservation as a common public good has the problem of indeterminate property rights, individuals in the community might attempt to free ride and take the advantages of others’ contributions. Based on factor extraction results, a set of indicators related to ”I think xxx should be responsible for soil and water conservation in the watershed” were loaded into this construct. So for landowners who obtained a higher factor score under this construct, they might be more likely to transfer their responsibilities to others in terms of BMP adoption. Therefore, the positive impacts from subjective norms on behavioral intention are not guaranteed in this kind of situation.

In the last part of our study, we applied cluster analysis to collect and analyze more nuanced information about landowner segmentation. It is worth noting that the number of clusters in the K-Means algorithm is an input parameter. Defining the number of clusters is often a subjective decision based on the interpretational interest of the researchers (Pouta et al., 2011). Overall, the segment socio-psychological differences produced by our cluster analysis would be useful in developing targeted conservation policy or educational or outreach approaches for various landowner types, and can also be used to assist observable characteristics classification, as well as geographic region classification.

According to the results from cluster analysis, we divided landowners into three groups: environmentally-conscious landowners (cluster 2), engaging-absentee landowners (cluster 0), and adoption-averse (cluster 1) landowners. The environmentally-conscious landowners (cluster 2) are statistically different from the other two clusters in terms of each TPB & DoI construct, and their intentions to three BMP adopting are also significantly higher. Demographically, they are relatively younger and have higher education. For engaging-absentee (cluster 0) and adoption-averse (cluster 1) landowners, in generally, they both care less about conservation, and have lower intentions to BMP adopting. However, the comparison of different constructs still reveal some interesting findings. Cluster 0 landowners have higher scores in terms of concerns, awareness, and favorable attitudes to BMP, while they have relatively low scores in behavioral control and past experiences. So it is likely that although they understand the benefits of BMP to conservation, they don't have enough economic and technological support to adopt BMP in action. In addition, landowners in cluster 0 are relatively older, with lower education and lower income.

The adoption-averse cluster is the opposite of the environmentally-conscious cluster in almost every construct, except under past experience dimension. They have a highest score in the dimension of "past experience", indicating that they may have participated in land management programs before. Unfortunately, it seems that they get more negative opinions about BMP from their previous experience, either due to the loss of economic income or the control of the land, or because of other reasons. Therefore, it's important for policy makers or environmental agencies to get feedback in time from landowners in the BMP programs, and to understand landowners' needs and concerns about the programs. Otherwise, they might turn into being averse to BMP adoption in the future.

Finally, we compare the proportions of landowners located in different geographic regions for each cluster to explore spatial heterogeneity. More than 50% of engaging-absentee (cluster 0) landowners are located in the south central part, where the monthly tax and the agricultural cash rental rates are relatively high. Cluster 1 and cluster 2 landowners are more evenly distributed in the regions, and the differences between them are not significant. However, the adoption-averse cluster (cluster 1) does have a larger proportion of landowners located in the west central region, where it has the largest number of impaired water bodies and the monthly tax value. On the other hand, the region Southwest has the least number of impaired water bodies and the lowest monthly tax value. Meanwhile, it has a relatively higher percentage of "environmentally conscious" landowners (cluster 2). With limited time and resources, we didn't continue with more sophisticated analysis to exam whether the latent separation follows clear geographic patterns. However, applying regional economics and environmental data to study the quantitative relationships between the regional characteristics and the landowner types would be beneficial to design targeted BMP policy and incentive mechanism. We will leave this part to further studies.

## *3.6 Conclusion*

Given the growing knowledge and technical skills in targeting strategies for conservation BMP, there is a pressing need to transfer the "optimal" or "cost-efficient" modelling solutions into BMP actions through public conservation policy. And in order to effectively motivate landowners' supportive behaviors towards conservation, policy makers need to understand landowners' characteristics that influence their intentions to adopt various BMP, emphasizing the importance of both observable and unobservable factors underlying landowners' decisions. Our study aimed at contributing to this need through identifying the unobservable social-psychological factors influencing landowners' intentions to wetland, cover crop and nutrient management BMP adopting. In addition, more nuanced landowner clusters comparisons, like the ones produced in this study, can provide insights into effective and efficient policy targeting and communication messages tailoring for distinct audiences to gather more support for BMP adoptions.

On the other hand, this growing demand for better understanding the unobservable drivers of behavioral intentions necessarily also introduces more challenges for economic valuation and incentive mechanism design in reality. It would be time- and cost- consuming to routinely collect landowners' socio-psychological attributes and to explore their roles in decision-making (Faccioli et al., 2018). When designing and/or evaluating conservation incentive programs, environmental economists, psychologists, and sociologists should work collaboratively to develop more solid frameworks of analysis and delineate improved and tailored scales for measuring the latent constructs. At the same time, establishing a bridge between the unobservable socio-psychological factors and observable demographic and geospatial information would be beneficial because the practitioners in conservation agencies will have much easier access to the latter type of data. Leveraging more advanced econometric techniques and emerging machine learning tools are necessary to solve this challenge.

# Chapter 4

# PREFERENCE HETEROGENEITY AND WILLINGNESS-TO-ACCEPT FOR CONSERVATION: A STATED PREFERENCE APPROACH FOR THE DESIGN OF INCENTIVE PAYMENTS

## *4.1 Abstract*

In the United States, voluntary incentive programs are the primary policy mechanism to improve sustainability of agricultural landscapes, employed to increase the supply of non-market ecosystem services alongside the provision of food and energy. Landowners' decision about whether to enroll in a voluntary incentive program is fundamentally the result of evaluating the alternatives based on their preferences and choosing the option that is most preferred. In this study, we adopted a survey approach to elicit agricultural landowner preferences, using results from our survey of Minnesota River Basin farmers. The data we collected were used to develop the distributions of individual-level willingness-to accept (WTA) compensations for the management actions considered (wetland restoration, cover crops plantation, nutrient management). Under the mixed logit specification, we characterized both observable and unobservable heterogeneity in the WTA estimation. Meanwhile, in keeping with established literature on the presence of non-pecuniary preferences among agricultural landowners, we studied the impacts on WTA from landowners' awareness and attitudes towards water quality and associated ecosystem services. On average, our findings suggest the total Willingness-to-Accept is around $400/acre for wetland restoration, $14/acre for cover crops, and $106/acre for nutrient management. These values are consistent with the incentive payment rates used by USDA Natural Resources Conservation Service. To explain the variation of WTA, our model found that the annual income and farm size of the respondents, as well as the re-

gional political leanings, monthly tax, and area of impaired water bodies all significantly contributed to the preference heterogeneity. At the same time, the appreciation of ecosystem services, past conservation experience, and the sense of responsibility all significantly influenced landowners preference for conservation.

## *4.2 Introduction*

Environmental degradation, such as water and air pollution, the depletion of natural resources, and global climate change, is one of the major societal threats faced by humanity (United Nations, 2004). To achieve the goal of sustainable development and overcome the "tragedy of the commons", it's crucial to change human behavior and actions in relationship to the environment (Polasky et al., 2019). Economics, combined with other social sciences, provide tools to study the motivation of individual and group behavior, and to design policies and institutions to shift behavior in pro-environmental directions.

Voluntary incentive programs are the primary policy mechanisms to reduce the nonpoint source of water pollution in agricultural landscapes across the nation (Kling, 2011a; Shortle and Horan, 2013). One of the central goals of the incentive instrument is to improve water quality and the provision of other non-market ecosystem services, while supporting agricultural production and rural livelihoods. However, as was pointed out by U.S. Government Accountability Office (2018), "existing incentive programs do not always sufficiently target the most cost-effective practices or locations". As a result, farmers can be overpaid relative to the benefits they provide, incentivized to make inefficient management choices, or insufficiently incentivized to participate, reducing the cost-effectiveness and hence, impact, of the policy (Claassen and Ribaudo, 2016). Under the framework of the incentive policy, landowners make independent choices about farm management based on the incentives, but also on personal preferences and values (Birol et al., 2006). The goal of this paper is to investigate the factors that influence farmers' preference for land conservation practices to inform potential policy improvements.

Specifically, we explore how different incentive designs can be adapted based on a discrete choice experiment (DCE) study on landowners' willingness-to-accept the incentive payments for implementing different land management practices. From our stated preference survey of landowners in the Minnesota River Basin, we collected the DCE data needed for estimating willingness-to-accept for three key management options: cover crops, nutrient management, and wetland restoration. We also collected a rich set of farmographic and sociodemographic characteristics to investigate the sources of heterogeneity, allowing for the estimation of factors hindering the likelihood of adoption of these management alternatives. In keeping with established literature on the presence of non-pecuniary preferences among agricultural landowners (Howley et al., 2015, 2014; Key and Roberts, 2009b), we also studied the socio-psychological attributes that represent amongst the most important drivers of people's behaviour towards the environment (Reimer et al., 2014; Dayer et al., 2016; Bennett et al., 2017). These socio-psychological attributes represent another layer of heterogeneity which will affect the compensation payments that landowners expected for adopting the land management practices on their lands.

Stated preference (SP) methods are widely applied in environmental economics as a means to collect information about respondent preferences for non-market environmental amenities of interest by observing choices in hypothetical situations presented in a survey (Carson and Czajkowski, 2019). One of the most commonly used tools to elicit preference information in an SP survey is discrete choice experiment (DCE). The technique is an attribute-based measure of non-market values, based on the assumptions that environmental goods or services can be described by their attributes and that an individual's valuation depends upon the levels of these attributes to maximize the individual's well-being ("utility"). Theoretical frameworks and details about DCE implementation and analysis can be found at Louviere et al. (2000); Hensher et al. (2005); Scarpa and Rose (2008).

In the design of agri-environmental incentive payment programs, the estimated willingness-to-accept (WTA) from DCE can be used to assess the costs and the supply of environmental benefits from implementing various environmentally beneficial management practices (commonly known as "Best Management Practices", or BMP). To improve the cost-effectiveness of incentive policy, one of the key issues to consider is the landowners' preferences heterogeneity about the BMP bundles and the potential payments. Previous studies haven show how differences in education, experience, primary occupation (farm or non-farm), and other socioeconomic characteristics, as well as land characteristics, can be important in the adoption of various conservation practices (Wu and Babcock, 1995; Yang et al., 2005; Duke et al., 2014; Cooper and Keim, 1996; Soule et al., 2000; Khanna, 2001; Lichtenberg, 2004). In addition, risk and uncertainty preferences (Kurkalova et al., 2006b), and possible transaction costs (Peterson et al., 2015) may play a role in adoption of conservation practices. In this paper, we characterize the heterogeneity by collecting individual level income, farm size and socio-psychological characteristics from survey questions, as well as county-level observable variables such as average tax payments, political inclination and water quality conditions that might account for the preference heterogeneity with the choice model.

## *4.3 Methods*

### *4.3.1 Study Site*

The Minnesota River Basin drains approximately 43,400 $km^2$ of south-central Minnesota, South Dakota, and Iowa. Following European settlement, native prairie has been replaced by agriculture and urban development, significantly altering the hydrology of the Minnesota River Basin (Gran et al., 2019). Dramatic increases in fertilizer input, coupled with the drainage of 80% of historic wetlands in the region since European settlement (Hansen et al., 2018; Gran et al., 2019), have contributed to high loads of nitrogen and phosphorus throughout the watershed creating numerous local and downstream water quality challenges, including increased soil erosion, substantial sediment, drinking water contamination, algal blooms, hypoxic zones, and harm to aquatic ecosystems in the Minnesota River, the Mississippi River and the Gulf of Mexico (Boardman et al., 2019). Furthermore, the Minnesota River Basin is part of the Midwest Corn Belt, one of the most productive and intensively managed agricultural regions in the world (Christensen et al., 2012). The basin stands out statewide as a top-producing region with 78% of land in farms, dominated by a field corn and soybean rotation ($\sim$ 93% of all acres) (Musser et al., 2009). To address concerns about degradation of water quality related to intensive agricultural activities, Federal and State of Minnesota programs have encouraged agricultural landowners to implement land conservation practices on private land by providing incentive payments through conservation programs such as the Conservation Reserve Program (CRP), the Environmental Quality Incentives Program (EQIP), the Reinvest In Minnesota Program (RIM), and the Minnesota Conservation Reserve Enhancement Program (MN CREP) (Ryan, 1985; Petri, 2014; Bramblett and Gillette, 2016).

### *4.3.2 Data Collection*

Landowners' decision about whether to enroll in a voluntary incentive conservation program is fundamentally the result of evaluating the alternatives based on their preferences and then choosing their preferred option. To examine the heterogeneity in landowners' preference about conservation programs, we conducted a stated preference survey of landowners in the Minnesota River Basin that addressed several key questions. First, we used an incentive-compatible dichotomous choice experiment to collect data for estimating willingness-to-accept (WTA) for three key management options: cover crops, nutrient management, and wetland restoration. Second, the survey collected farm and sociodemographic characteristics for exploring the preference heterogeneity from observable variables. Finally, a set of behavioral and attitudinal data regarding landowners' attitudes and perceptions about the conservation practices and regional ecosystem services were also collected. These data could then be used to estimate the effects from unobservable preference heterogeneity on compensating differentials.

Human subjects approval for the survey was granted by the Human Subjects Review Board of the University of Washington (IRB ID: STUDY00003970). Participants of our survey were recruited through a B2B crop grower panel, purchased through Survey Sampling Inc.TM, which generally represent the agricultural landowner population within the

Minnesota River Basin. The survey was pre-tested with cognitive interviews (n = 4) though teleconference phone calls and with a mailed/online pilot study (n = 100). Using the pilot responses as starting values, Ngene software (Metrics, 2012) was applied to create the D-efficient choice sets (D-error = 0.270). In our survey, each participant had eight choice cards that were presented in a random order for the choice experiment. Along with that, we developed a quantitative, structured questionnaire, which included farmographic and demographic questions, as well as indicators for assessing the behavioral-attitudinal constructs such as attitude, social norms, perceived behavioral control, and compatibility, according to the environmental psychology literature (Wauters et al., 2010; Ulrich-Schad et al., 2017; Westlake, 2019). A total of 1920 people received our final survey and 441 of them replied with usable data, resulting in an effective response rate around 23%.

### *4.3.3 Discrete Choice Experiment*

Discrete choice experiment (DCE) is developed within the framework of the random utility model. It assumes that the utility derived from goods or services is a function of the particular attributes and corresponding levels comprising it, and individuals' decision-making are based on utility maximization. In each choice scenario, participants would face two or more alternatives where at least one attribute of the alternative is systematically varied such that information related to preference parameters of an indirect utility function can be inferred.

In our DCE, individual $i$ faces a choice among two alternatives ($j$ = Incentive Program VS. Status Quo) in eight independent choice situations (t = 1, 2,. . . , 8, see Table 4.1).

Each alternative has four attributes. The first three attributes represent three types of land conservation practices: wetland restoration, cover crop plantation, and nutrient management adoption. They all had two levels "Yes" VS. "No", indicating whether the certain land conservation practice is included in the incentive program or not. The fourth attribute is the incentive payment, which is the amount of hypothetical payment landowners will get for participating in the incentive program. The payment levels are designed based on the ratio (0.5, 1, 1.1 or 1.3) adjusted USDA Natural Resource Conservation Service Payment

Schedules for a specific practice. Landowners will not get paid if they choose the Status Quo alternative. Note that the comparisons between the Incentive program and Status Quo is restricted to the ones in the same choice scenario. More formally, we write the utility of individual landowner $i$ for choosing alternative $j$ in the choice scenario $t$ as:

$$U_{ijt} = U(X_{ijt}, \epsilon_{ijt}) \tag{4.1}$$

where $X_{ijt}$ is a vector of observable attributes for an alternative that is presented to respondent in the choice situation $t$. $\epsilon_{ijt}$ is a random component of preferences only known to the individual respondent but not observed by the researcher. Utility can further be specified as additively separable in the observable component $V(\cdot)$ and the random component.

$$U_{ijt} = V(X_{ijt}) + \epsilon_{ijt} \tag{4.2}$$

### *4.3.4 Behavioral and Attitudinal Factors Analysis*

In our survey, landowners' behavioral-attitudinal attributes were ascertained through two types of questions. On the one hand, we designed a set of statements related to ecosystem services, land management practices, and watershed protection. Landowners were asked to indicate their degree of agreement or disagreement on a 5-point Likert Scale. On the other hand, we had a set of "check all that apply" questions, asking landowners' consumption of ecosystem services, their past conservation actions, and their opinions about watershed environmental problems and conservation responsibilities. Since we had both the Likert-scale data and the dichotomous categorical data, we conducted factor analysis separately for them. Applying both exploratory factor analysis and confirmatory factor analysis, we extracted the latent variables related to environmental attitudes, social norms, perceived behavioral control and compatibility, which, according to the TPB & DoI theories, would affect landowners' intentions to adopting conservation practices.

Table 4.1: Choice Scenarios

| Choice Scenarios | Alternatives | Wetland Restoration | Cover Crops | Nutrient Management | Payment |
|---|---|---|---|---|---|
| 1 | Voluntary Program | Yes | Yes | Yes | 600 |
| | Status Quo | No | No | No | 0 |
| 2 | Voluntary Program | No | Yes | No | 50 |
| | Status Quo | No | No | No | 0 |
| 3 | Voluntary Program | Yes | No | No | 650 |
| | Status Quo | No | No | No | 0 |
| 4 | Voluntary Program | No | No | Yes | 25 |
| | Status Quo | No | No | No | 0 |
| 5 | Voluntary Program | Yes | Yes | Yes | 500 |
| | Status Quo | No | No | No | 0 |
| 6 | Voluntary Program | No | No | Yes | 450 |
| | Status Quo | No | No | No | 0 |
| 7 | Voluntary Program | No | Yes | No | 150 |
| | Status Quo | No | No | No | 0 |
| 8 | Voluntary Program | Yes | No | No | 200 |
| | Status Quo | No | No | No | 0 |

Note: There are eight dichotomous choice scenarios (T=8) and each respondent makes decisions between two alternatives. In the Voluntary Program, three management actions compose a land conservation practice bundle with a potential payment for adopting these practices. The payment levels are based on the adjustment of USDA NRCS payment schedules. The status quo condition stands for "doing nothing and no payment". The desirability of the Voluntary Program compared with Status Quo condition are expected to change with the incentive payment amounts and with which land practices that are offered in the program.

### *4.3.5 Econometric Analysis*

From the Random Utility standpoint, landowner $i$ is willing to accept the incentive payment in the voluntary program if and only if their utility with the voluntary incentive program exceeds the utility for the Status Quo condition. Since the random component is unknown from the researcher's perspective, the preference for an alternative is manifested through probability. So if we define $y_{ij} = 1$ as the event of choosing the alternative $j$ and assume a linear utility function, then the probability is:

$$Pr(y_{ij} = 1) = Pr(V_{ij} + \epsilon_{ij} > V_{iq} + \epsilon_{iq}) = Pr(\beta' X_{ij} + \epsilon_{ij} > \beta' X_{iq} + \epsilon_{iq}) \tag{4.3}$$

which can also be written as

$$Pr(y_{ij} = 1) = Pr(\epsilon_{iq} - \epsilon_{ij} < \beta' X_{ij} - \beta' X_{iq}) \tag{4.4}$$

Where $\beta$ is a vector of coefficients associated with $X_{ij}$ capturing both the attributes relating to the $j$th choice, and that of the individual $i$ (i.e.socio-demographic and behavioral-attitudinal characteristics of the $i$th participant). Since we assume landowners' preference varies across each other, a mixed logit (MXL) model is applied to capture the preference heterogeneity by allowing the coefficient $\beta$ to vary according to a distribution around its mean value. Under a linear specification of the utility, we expand the equation as:

$$U = X\beta_x + Z\beta_z + \text{ASC}\beta_{ASC} + \epsilon \tag{4.5}$$

The utility function consists of four components: $\beta_x$ is a vector of coefficients associated with the choice attributes in the discrete choice experiment. $\beta_z$ is a vector of coefficients representing individuals' idiosyncratic characteristics, from both the observable and unobservable sources. The random error $\epsilon$ is assumed as independent, identical and following the Type I Extreme Value distribution. The parameter Alternative Specific Constant (ASC) is the intercept in the model, representing the impacts to utility coming from other factors not included in the model. The ASC is specified to be one when the Incentive Program is chosen and zero when the respondent opted for Status Quo.

Three econometric models were estimated. The first model only had the attributes of the choice experiment as explanatory variables, the second model incorporated socio-demographics information, and the third one considered both the socio-demographics and socio-psychological characteristics as the potential sources of preference heterogeneity. Table 4.2 presents the description of variables used in the mixed logit models. For ease of interpretation, all categorical variables in the models are dummy coded. Finally, the results from MXL models were converted into more tangible monetary quantities by calculating the WTA values for each of the conservation practice attributes. The marginal WTA is derived as the marginal rate of substitution between the compensation payment attribute $p$ and another land conservation attribute $m$, holding all else constant, and it can be calculated as the negative of the ratio between the two parameters $\beta_m/\beta_p$ (Mitchell et al., 1989; Louviere et al., 2000). Note that the negative sign serves to amplify the WTA for positive utility changes associated with the payment provision, given that we expect positive preferences for the compensation payment ($\beta_p > 0$) and negative preferences for the conservation practice ($\beta_m < 0$).

Following Giraud et al. (1999); Obeng and Aguilar (2018), we also calculated the expected total WTA, representing the minimal payment that the survey respondent will accept to make her as well off as when she agrees to implement the land management actions (Incentive program) and when she rejects the program in favor of the current situation (Status quo). In other words, the total WTA is defined by $U_{VP} = U_{SQ}$. Expanding the utility functions with full set of parameters, we have:

$$\begin{gathered}
\text{WTA}\beta_p + X^{-p}\beta_x + Z\beta_z + \text{ASC}\beta_{ASC} + \epsilon_{VP} = 0 + \epsilon_{SQ} \Rightarrow \\
\text{WTA}\beta_p + X^{-p}\beta_x + Z\beta_z + \text{ASC}\beta_{ASC} + = \epsilon_{SQ} - \epsilon_{VP}
\end{gathered} \tag{4.6}$$

Where $X^{-p}$ denotes the attributes of the choice experiment alternatives except the payment attribute. Since the difference in error terms has zero expectation, the expectation of the total WTA can be written as

$$E\big[\text{WTA}_n\big] = \frac{-\big[X^{-p}\beta_x + Z\beta_z + \text{ASC}\beta_{ASC}\big]}{\beta_p} \tag{4.7}$$

The expected total WTA represents the critical payment for the respondent to participate in the voluntary incentive land management program. In conservation policy design or decision-making, it provides one of the cost information that captures landowners' preference heterogeneity. By conditioning WTA estimates on the individual or area-defined characteristics such as farm size and income, we aim to simulate policies that can provide sufficient incentives (avoid over-payment or insufficient incentives) according to landowners' preferences and the environmental benefits they provide, and to assist cost-efficient targeting. After estimating the coefficients, we conducted a series of microsimulation to quantify the dispersion of WTA considering the uncertainties introduced during the mixed logit estimation process. With the help of Monte Carlo techniques, a parametric bootstrap method Krinsky-Robb (Krinsky and Robb, 1986) was used to quantify the statistical uncertainty around each estimated WTA point by constructing the confidence intervals and sampling distributions.

### *4.3.6 Up-scaled WTA Simulation*

In the integrated optimization model that aims to generate benefit-cost Pareto frontiers to analyze policy efficiency, the total expected WTA, as one of the cost inputs, reflects landowners' preference heterogeneity. Due to the confidentiality issue, however, at the benefit side, most of the spatial data about farms and the results from biophysical models are usually delivered at regional level. This requires us to scale up and construct spatially varying estimates of WTA that can be coupled with a biophysical model. In other words, we want the WTA estimates to be compatible with the biophysical data so that they can be used together in optimization model for designing cost-efficient conservation allocations in the Basin.

For our study, we used a biophysical modeling framework that combines a simplified river network model (NNM) (Czuba et al., 2018) with an existing calibrated and validated Soil Water and Assessment Tool (SWAT) model of the Minnesota River Basin. The model divides the Minnesota River Basin into 515 individual subbasins and quantifies nitrate-nitrogen and sediment concentrations for each subbasin as they respond to changes in management practices. Ideally, with the coefficients estimated by the MXL model, we can scale the expected WTA up to the subbasin level by including observable characteristics in the specification of the observed component of utility. However, it's difficult to find the sociodemographic and economic data that perfectly match the individual subbasin. Instead, the data are usually only available at the county level. Therefore, to simulate the up-scaled cost, we first find the county-level observable variables accounting for the preference heterogeneity within the choice model and estimate the county-level expected WTA. Then, we scaled the estimates to subbasin-level based on the spatial relationships between the subbasins and counties. For subbasins located within a single county, the subbasin-level WTA would be the same as the county-level WTA. For subbasins across multiple counties' boards, the subbasin-level WTA will be the spatially weighted average of the county-level WTA.

## *4.4 Results*

### *4.4.1 Survey Participants*

Our final sample included 441 complete surveys. Socio-demographic characteristics from the sample were compared against the Minnesota Agricultural census data (NASS, 2017) to check for representativeness. In general, the demographic make-up of our survey respondents was fairly representative of the averages associated with Minnesota agricultural census.

Our sample panel was made up of 78.2% male versus 20.4% female, which was consistent with the census record of 73.7% male versus 26.3% female. In terms of age, 53.5% of our sample fell in the age category 50-70, and 23.5% were above age 70. According to the census data, the average age of the Minnesota's farm operators is 56.4, with 54.7% in the age category 45-64, 27.2% above age 65. For farm size, 47.6% of our respondents have farmland 100-500 acres, 13.4% have 500-1000 acres, and 7.3% have more than 1000 acres. The distribution is also similar to the census data (51.4% for 50-500 acres, 10.4% for 500-1000 acres, and 9.3% for more than 1000 acres). When it comes to annual income, our sample had a smaller share of low-income landowners than the census data. 12% of survey respondents had income less than $25,000, 18% were between $25,000 to $99,999, and 46% for income over $100,000. In the census data, the shares are 51%, 16.3% and 32.6% respectively for the corresponding income categories.

The descriptions of the socio-demographic characteristics of our sample are presented in Table 3.1 and Figure 4.1.

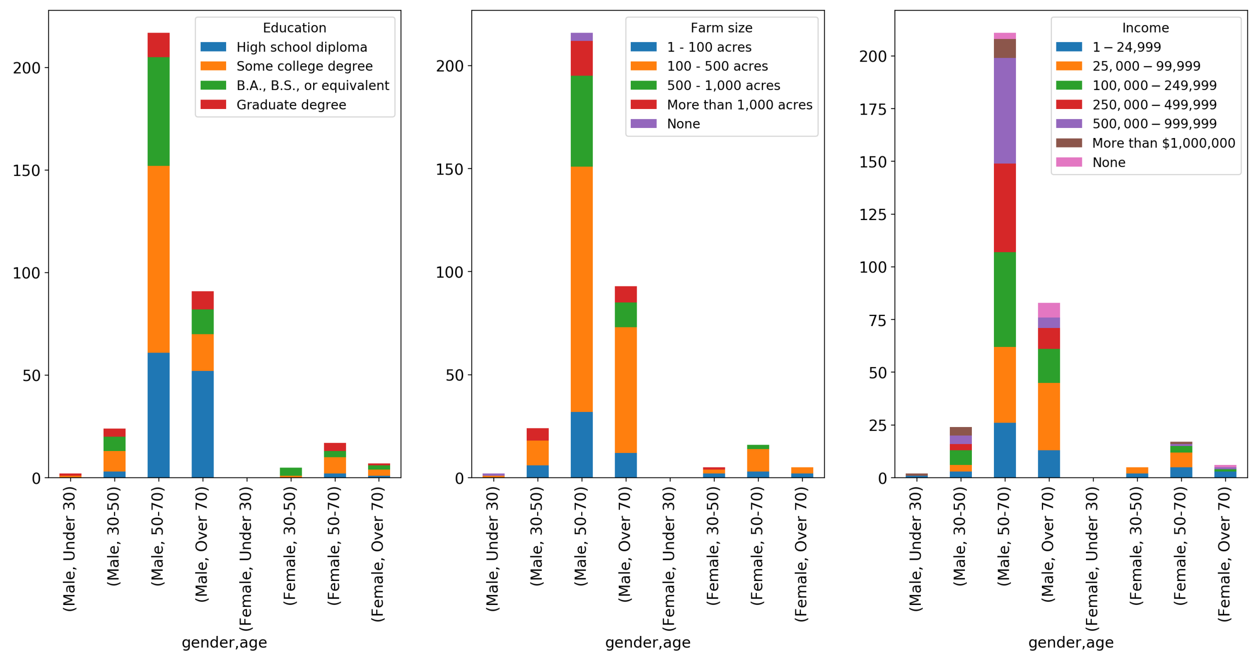


Figure 4.1: Socio-demographic characteristics of the survey sample

### *4.4.2 Sources of Preference Heterogeneity*

The socio-demographic characteristics represent one of the important sources of observable preference heterogeneity. The measurement of unobservable preference heterogeneity related to behavioral-attitudinal factors is usually done by collecting various indicators for extracting latent variables. From our survey, a set of indicators, revealing various attitudes, awareness about the environment, past conservation experience, and social norm have been collected. We first performed an exploratory factor analysis on the indicators to test for evidence of reliability and validity of the measurement instrument, and then applied a confirmatory approach to confirm the evidence and estimated factor scores for each individual. A detailed factor analysis regarding our survey data can be found at Table 3.2 and Table 3.3.

After the model selection process, we incorporated four of the behavioral-attitudinal factors in our econometric model: awareness about environmental problems, appreciation of ecosystem services, past experience of conservation practices, and sense of responsibility for water conservation.

In addition to the individual level characteristics from the survey questions, we also explored county scale observable variables that might account for the preference heterogeneity with the choice model. According to the Akaike Information Criterion (AIC) model selection results, county level 2017 monthly average tax payments, political voting records from 2008-2018, and the areas of impaired lakes are included in our utility function. Table 4.2 shows the descriptive statistics of county-level variables and the behavioral-attitudinal characteristics we obtained for eliciting preference heterogeneity.

Table 4.2: Descriptive statistics of county-level variables and the behavioral-attitudinal characteristics

| Variable | Description | Mean | Standard Deviation |
|---|---|---|---|
| Tax | Monthly tax costs | 483.67 | 116.73 |
| Political_votes | Percentage of voting for Democrats | 0.523 | 0.057 |
| Impaired_lake | Impaired lake areas/1000 (re-scaled) | 2.769 | 3.698 |
| AWARE | Awareness of environmental problems (latent, normalized) | 0.94 | 0.32 |
| PAST | Past experience of conservation actions (latent, normalized) | 0.52 | 0.26 |
| APP | Appreciation of ecosystem services (latent, normalized) | 0.20 | 0.15 |
| RESP | Sense of responsibility to conservation (latent,normalized) | 0.16 | 0.13 |

### *4.4.3 Model Estimation*

Table 4.3 presents the results of three MXL models: the basic MXL model only considering DCE attributes, the MXL model with socio-demographics characteristics, and the MXL model including both socio-demographics and behavioral-attitudinal characteristics. All of the three models produce statistically significant coefficients for the DCE attributes. The conservation practice attributes: wetland, cover crop and nutrient management are all significant and negative, meaning that landowners would be averse to the conservation program but opt for the status quo when keeping other factors the same. The positive sign in front of the payment attribute indicates that respondents have clear preferences for the incentive payment. This indicates the systematic importance of the compensation payment attribute in predicting whether landowners choose to participate in conservation programs versus sticking with the status quo.

Under the mixed logit framework, the DCE attributes are treated as random parameters drawn from specific distributions, indicating that not every respondent reasons the same. In our models, we imposed an exponential distribution to all DCE attributes, and specified the environmental characteristic variable LK (impaired lake areas at county level) to be interacting with the means of DCE conservation practice attributes. The estimates had expected signs and were statistically significant for the means of cover crop, indicating that the impaired environment situation might improve the preference on adopting cover crops, keeping all other variables constant.

The demographic and attitudinal information (Models 2 and 3) did enhance model fitness as denoted from AIC values and overall goodness of fit (pseudo-R2). Meanwhile, the statistically significant standard deviation parameters for all of the socio-demographic and behavioral-attitudinal characteristics confirmed the various sources of preference heterogeneity in addition to DCE attributes.

For the observable socio-demographics characteristics, at county level, the political leaning for Democrats had a significantly positive influence on the choice for the conservation program; while the monthly tax costs negatively affected the probability, all other things being equal. At individual level, the highest income category was taken as the baseline for comparison. The result indicated that landowners with relatively low income were more likely to choose the conservation program alternative. In other words, all else constant, landowners with higher income would demand a higher compensation payment for adopting land conservation practices. The land size dummy variables were compared to the smallest land size category. The positive and statistically significant coefficients reflected a higher

Table 4.3: Mixed logit model estimates (+/- SE) comparisons. Note: in terms of interpreting the coefficients, negative signs indicated having a negative impact on choosing the Voluntary Program

| Coefficients | MXL1: only choice attributes | MXL 2: choice attributes + socio-demographic variables | MXL3: choice attributes + socio-demographic + psychological variables |
|---|---|---|---|
| Wetland | -1.853(0.220)*** | -1.887 (0.224) *** | -1.815(0.221)*** |
| Cover Crop | -0.482(0.127)*** | -0.494 (0.125) *** | -0.450(0.123)*** |
| NutrientManagement | -0.768(0.130)*** | -0.785 (0.130) *** | -0.706(0.128)*** |
| Pay | 0.00381(0.00026)*** | 0.00388 (0.00026) *** | 0.0038(0.00026)*** |
| | Heterogeneity | | |
| ASC | 0.215(0.076)*** | -2.316 (0.378) *** | -2.731(0.395)*** |
| *Political_votes* | - | 4.592(0.611) *** | 4.663(0.632)*** |
| *Tax* | - | -0.001 (0.0003) *** | -0.0009(0.0003)*** |
| *Income_1* | - | 0.414 (0.168) ** | 0.604(0.171)*** |
| *Income_23* | - | 0.427 (0.166) ** | 0.763(0.175)*** |
| *Income_4* | - | 0.342 (0.169) ** | 0.569(0.75)*** |
| *Income_5* | - | 0.403 (0.176) ** | 0.562(0.184)*** |
| *Income_6* | - | 1.533 (0.337) *** | 2.201(0.371)*** |
| *Landsize_2* | - | 0.373(0.122) *** | 0.359(0.121)*** |
| *Landsize_3* | - | 0.150 (0.133) | 03293(0.134) |
| *Landsize_4* | - | 0.218 (0.090) *** | 0.260(0.092)*** |
| *F_aware* | - | - | 0.089(0.128) |
| *F_past* | - | - | 0.503(0.118)*** |
| *F_app* | - | - | 1.492(0.209)*** |
| *F_resp* | - | - | 1.082(0.250)*** |
| | Heterogeneity in mean | | |
| Wetland : *Impaired_lake* | -0.032 (0.044) | -0.032 (0.045) | 0.039(0.045) |
| CoverCrop : *Impaired_lake* | 0.0981 (0.027)*** | 0.096 (0.027) *** | 0.096(0.028)*** |
| NutrientManagement : *Impaired_lake* | -0.010 (0.024) | -0.012(0.025) | -0.017(0.025) |
| Log likelihood function | -1661.3 | -1641.93 | -1603.837 |
| Pseudo R-squared | 0.091 | 0.103 | 0.125 |
| AIC | 3338.6 | 3319.9 | 3277.4 |
| ***, **, * ==>Significance at $\alpha = 0.01$, 0.05, 0.10, respectively | | | |

probability of participation over the status quo as the land size increased, holding other things constant.

The lowest AIC and highest pseudo R-squared implied that Model 3 better fit the outcome data than Model 1 and Model 2, and confirmed the significant effects of the behavioral-attitudinal factors on decision making. Consistent with expectation, a higher score in the dimensions of PAST EXPERIENCE, APPRECIATION and SENSE OF RESPONSIBILITY all resulted in a higher probability of choosing the conservation program relative to the status quo option when keeping all other factors the same. Meanwhile, when comparing the Model 3 and Model 2, we found that the behavioral-attitudinal factors had not changed the effects from the observed socio-demographics characteristics on decision making.

### 4.4.4 Willingness-to-Accept Estimates

Table 4.4 reports the average of MWTA, the amount of compensation payment someone would accept for one unit increase in the conservation practice adoption.

Table 4.4: Marginal willingness-to-accept estimated for conservation practices. Note: Numbers in square brackets are 95% confident intervals obtained with Krinsky-Robb method using 1000 replications from the distribution with coefficients and covariance matrix estimated from the mixed logit models.

| Marginal WTA | Wetland | Cover Crops | Nutrient Management |
|---|---|---|---|
| Model 1 | 487.02 [483.92, 490.19] | 101.49 [99.51, 103.34] | 201.73 [199.77, 204.12] |
| Model 2 | 487.32 [484.45, 490.41] | 103.07 [101.25, 104.87] | 202.85 [201.04, 204.91] |
| Model 3 | 478.02 [474.60, 481.14] | 91.18 [89.19, 92.92] | 185.80 [183.89, 187.79] |

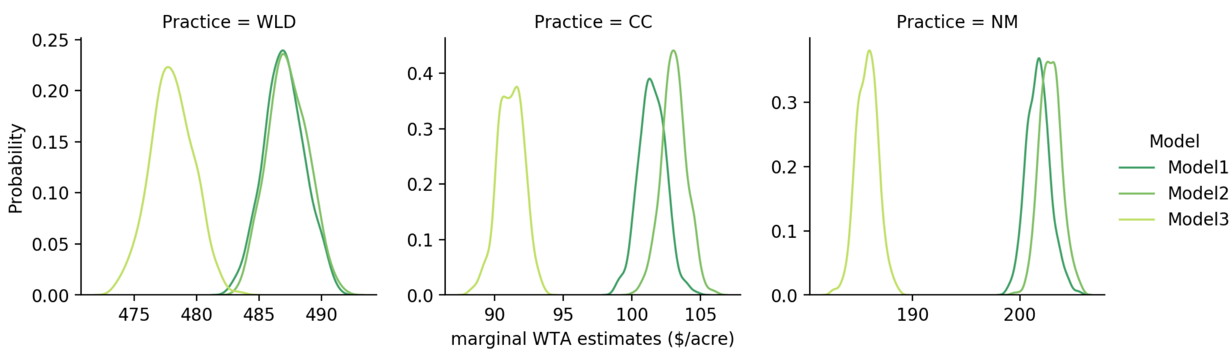


Figure 4.2: The distributions of simulated marginal WTA for WLD(wetland), Cover Crop(CC) and Nutrient Management(NM)

The pattern between the MWTA is similar for all the three models. Basically, wetland restoration requires the highest incentive compensation for each additional restoration, which is around \$480. The value for cover crops and nutrient management is around \$100 and \$200 respectively. Meanwhile,compared with estimates from Model 1, the predicted MWTA from Model 2 were significantly higher (dependent t test $p < 0.05$ for WLD, $p < 0.001$ for CC and NM), while the ones from Model 3 were significantly lower (dependent t test $p < 0.001$ for WLD, CC and NM).

In addition to the marginal willingness-to-accept, we also constructed the distributions of the total willingness-to-accept (TWTA) that represented the researchers' expected critical payment (mandatory or voluntary) which made an average respondent just indifferent between the conservation program and the status quo. Table 4.5 reports the TWTA for three conservation practices attributes based on the coefficients estimated from different models. Figure 4.3 displays the distributions of the estimated TWTA.

Table 4.5: Total willingness-to-accept ($/acre)

| Total WTA | Wetland | Cover Crops | Nutrient Management |
|---|---|---|---|
| Model 1 | 429.78 [323.64, 536.01] | 44.17 [-5.08, 92.29] | 144.42 [77.12, 208.86] |
| Model 2 | 394.62 [261.99, 526.38] | 10.43 [-82.98, 101.70] | 110.17 [4.37, 212.21] |
| Model 3 | 403.90 [264.20, 543.43] | 16.95 [-86.16, 118.28] | 111.53 [-3.06, 221.98] |

Model 1 only included the DCE attributes and ASC. The TWTA value based on Model 1 estimates was significantly higher than the results based on Model 2 and Model 3. Also, the distribution was much more concentrated closely near the mean. The average TWTA estimates based on Model 2 and Model 3 were not significantly different, although the shapes of the TWTA distributions from Model 3 were much wider, indicating a higher level of uncertainty. This was somewhat expected since both socio-demographics and socio-psychological variables were added to the model to account for preference heterogeneity. It should be emphasized that, although both MWTA and TWTA provide useful information about the necessary compensation for conservation provision, only TWTA includes the characterization of preference heterogeneity, and therefore is more relevant to the conservation costs estimation.

Note that there were some negative estimates of TWTA from Model 2 and Model 3, revealing the situations when landowners had strong aversion to the status quo, and were willing to adopt conservation practices even in absence of compensation payment. This might stem from a belief that conservation projects were beneficial to the whole community or from pride farmers take as a good stewardship in protecting the watershed. It could

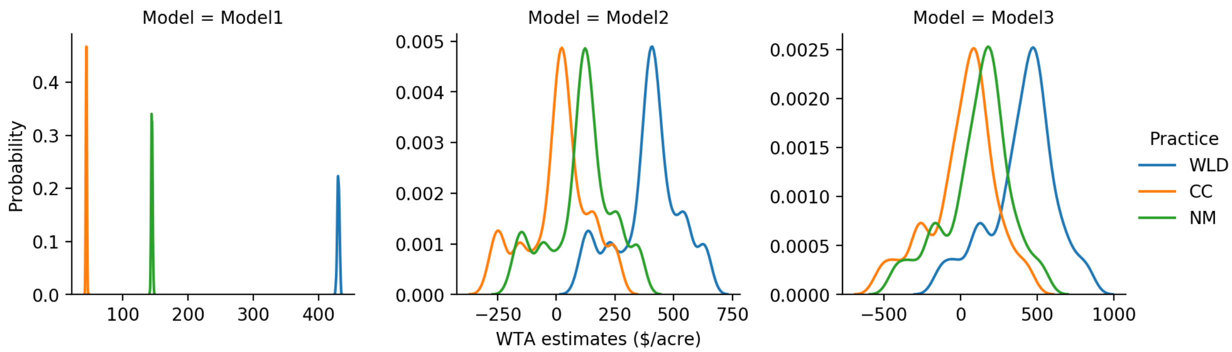


Figure 4.3: The distributions of simulated total WTA for WLD(wetland), Cover Crop(CC) and Nutrient Management(NM)

also indicate the presence of non-pecuniary preferences among landowners that have not been captured by our current models. Overall, the TWTA estimates from our models were fairly compatible with the payment rates for the incentives conservation programs in reality as well as the regional cropland cash rental rates. For example, the compensations listed in the payment schedule of Environmental Quality Incentives Program (EQIP)-Minnesota arrange from \$313.33 to \$580.96 for wetland restoration, \$22.33 to \$71.90 for cover crop, and \$4.81/acre to \$258/acre for Nutrient Management (NRCS, 2020).

### *4.4.5 County Level Willingness-to-Accept & Benefit-Cost Simulation*

Our TWTA estimates from Model 2 and Model 3 were not significantly different. However, the socio-psychological variables in Model 3 are difficult to observe for integrated basin-scale modeling. Therefore, we chose the utility specification of Model 2 (only include the observable socio-demographic variables) and applied the county-level data to scale the WTA heterogeneity up to the county- and subbasin-level. Based on our utility specification, the monthly average tax payments, voting records, and the area of impaired lakes were already county-level. Here, we only needed to substitute the individual-level income and farm size distributions with the county-level data.

We built the distributions of the income and farm size for each county within the Minnesota River Basin using the county-level agricultural economics data published in Finbin, a public farm financial database developed by University of Minnesota. Figure 4.4 shows the the county-level WTA estimates simulated from Krinsky-Robb parametric bootstrap using the county-level data.

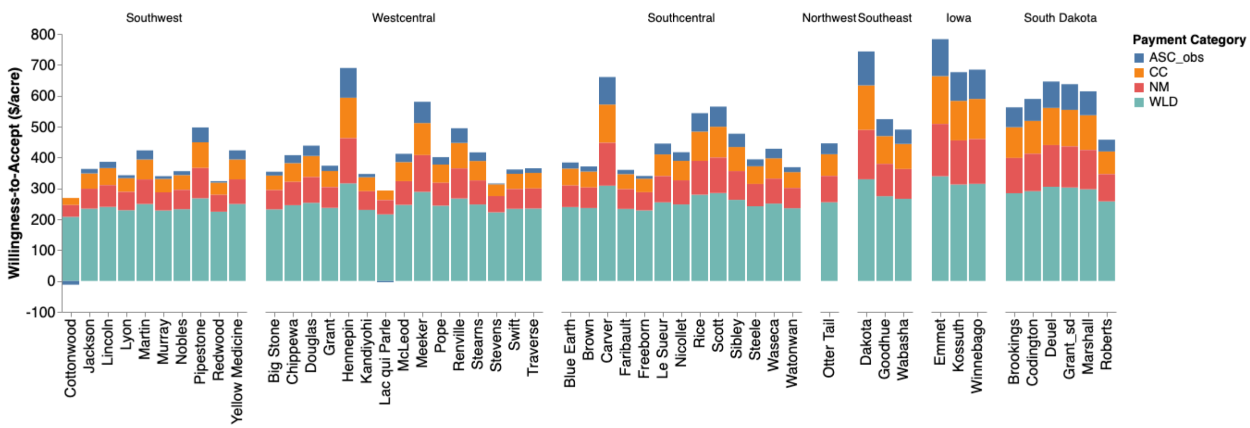


Figure 4.4: County-level WTA estimates

Next, we integrated the WTA estimates with a biophysical model to account for farmers' management decisions at a scale relevant to the heterogeneity of the biophysical processes. The biophysical model we applied simulated the biophysical consequences of 515 subbasins in response to the land management scenarios. To be compatible with the biophysical model, we modified the county level WTA to the subbasin level based on the locations of the subbasins relative to the counties (see Figure 4.5).

In Chapter 2, we have shown that ranking decision-making units based on weighted benefit-cost ratios (wBCR) is quite efficient in terms of finding cost-effective locations. Here, we followed the same logic to construct the wBCR for each subbasin, and then ranked the subbasins based on wBCR to indicate their relative cost-effectiveness. We constructed the costs for a management practice (take wetland restoration as an example) using the expected TWTA and the corresponding engineering costs, which were estimated based on the restoration and maintenance costs assumptions (MNPCA, 2017a,b). Meanwhile, the NNM

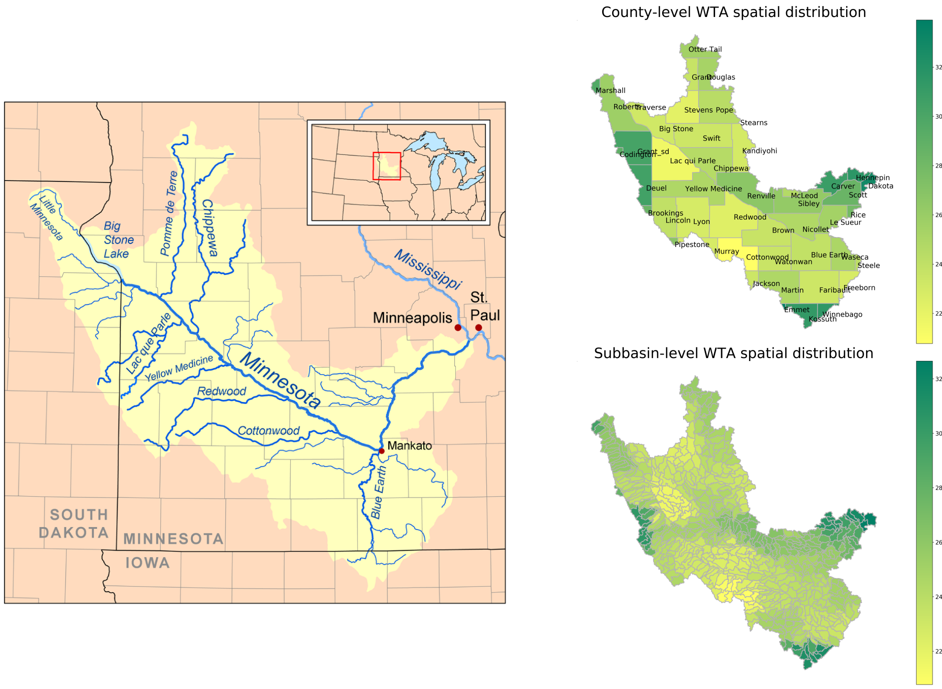


Figure 4.5: Left: Location of Minnesota River Basin(Kmusser, 2008). Right: Scaled WTA spatial distributions (wetland WTA as the example)

+ SWAT biophysical model quantified the nitrate-nitrogen and sediment concentrations for each subbasin as they respond to wetland restorations. With the costs data and biophysical simulation results, we have constructed the weighted benefit-to-cost ratio (wBCR) for each subbasin, where the weight $\lambda$ represents the relative importance of sediment reduction over nitrogen reduction in the wBCR ranking. To show a spatial pattern of the cost-effectiveness, we displayed the subbasin average wBCR in Figure 4.6. The darker of the color, the more cost-efficient of the subbasin.

Meanwhile, after obtaining the location-specific wBCRs, we ranked them in a descending order, and computed the wBCR difference (referred as "wBCR distances") between the adjacent positions in the ranked wBCR sequences as the metric to calibrate the resistance of the site in maintaining the prioritization in decision making. The greater the wBCR distance, the more resistant the location is in keeping its priority. This approach is related to robustness analysis and allows us to identify the locations that are likely to remain cost-efficient even if the optimization assumptions represented by the biophysical and the economic model do not hold. Figure 4.7 shows the spatial distribution of the subbasin wBCR distances.

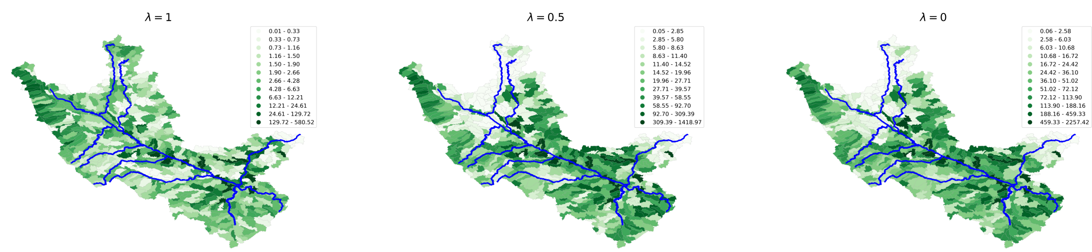


Figure 4.6: wBCR spatial distributions for three management scenarios. Note: $\lambda$ represents the relative importance of sediment reduction over nitrogen reduction in the wBCR ranking for the certain scenario. The darker of the color, the more cost-efficient of the subbasin. For visualization purpose, the legend is re-scaled by $10^3$.

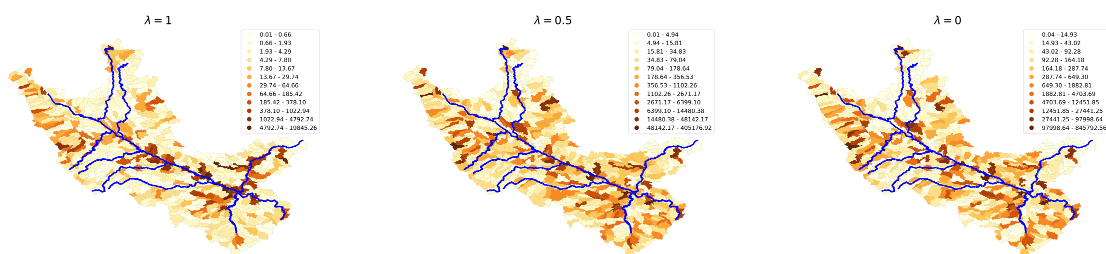


Figure 4.7: wBCR distance spatial distributions for three management scenarios. Note: $\lambda$ represents the relative importance of sediment reduction over nitrogen reduction in the wBCR ranking for the certain scenario. The darker of the color, the more resistant of the subbasin in maintaining its priority in the wBCR ranking. For visualization purpose, the legend is re-scaled by $10^3$.

From the choropleth maps of both the subbasin average wBCR (Fig 4.6) and average wBCR distances (Fig 4.7), one can see that for scenario $\lambda = 1$ (only focus on sediment reduction), the subbasins lying along the flow path of the Minnesota River (Minnesota State's largest tributary to the Mississippi River and is labeled as one of the most polluted rivers in the nation) have greater wBCR and wBCR distances than others, indicating these locations may deserve higher priority in cost-efficient conservation policy design. For scenarios $\lambda = 0$ (only focus on NO3 reduction) and $\lambda = 0.5$ (equal weight on both sediment reduction and NO3 production), subbasins alongside the flow path of Minnesota River also show relatively higher wBCR ranking and wBCR distances (robustness). Meanwhile, the south-central tributary areas concentrate with more cost-efficient and robust subbasins. These subbasins mainly lie within the Greater Blue Earth River Basin, which has historically exported a disproportionately large amount of sediment compared to surrounding basins. By volume, the Blue Earth is the Minnesota River's largest tributary (Fig 4.5 Left), which delivers around 46% of the flow in the Minnesota River, 55% of the suspended sediment load, and 69% of the nitrate-nitrogen load (GBERBA, 2020).

### *4.5 Discussion*

The prevalence of non-point sources as primary drivers of water quality challenges in the Minnesota River Basin poses an additional challenge to the 'supply-side' of clean water. Motivating landowners to provide water conservation services requires understandings of their preferences for these land conservation programs. In this study, we employed a discrete choice experiment (DCE) and mixed logit modeling to investigate how the program attributes, individual and regional characteristics would affect landowners' preferences and Willingness-To-Accept (WTA) for wetland restoration, cover crop, and nutrient management. Understanding the sources of preference heterogeneity would help policymakers structure incentives to promote pro-environmental behaviors more effectively.

The DCE results from our study show the role of compensation payments for incentivizing farmers' participation in the land conservation programs. From Model 1, which only considered the conservation practice and payment attributes, it's clear that landowners would not be willing to adopt the conservation practices without payment. The minimal willingness-to-accept for landowners for participation was around \$430/acre for wetland restoration, \$44/acre for cover crops plantation, and \$144/acre for nutrient management. The ASC in Model 1 was positive and statistically significant. However, the ASC terms in Model 2 and

Model 3 turned into negative and significant, indicating a general aversion to the incentive conservation programs but opt for status quo. The negative ASC, identified up to the difference in intercepts in the indirect utility function due to the arbitrary scaling of utility, was considered as a form of status quo bias (Samuelson and Zeckhauser, 1988) or endowment effect (Kahneman and Knetsch, 1992) that could be due to the mistrust and doubts about the administration, complexity of the choice task, uncertainty about the trade-offs, or a protest against the survey (Adamowicz et al., 1998; Meyerhoff et al., 2009). In real practice, from the perspective of environmental agencies, the negative ASC can refer to the fixed costs of recruiting. Since farmers are reluctant to participate, the environmental agencies will have to spend labor and money on events like workshops and stakeholder meetings for the conservation programs education and promotion.

To explore the impact of factors other than DCE attributes, we incorporated both the socio-demographics and socio-psychological variables in the MXL models (Model 2 and Model 3) to account for landowners' preference heterogeneity. We have shown that demographic information like income, farm size, political leaning and monthly tax level all contribute to the observed preference heterogeneity. In general, we found that landowners with lower income, larger farm size, and in counties leaning to Democrat and have lower-monthly tax levels are more likely to choose the incentive conservation program. It should be noted that the effects from income and farm size work in different directions and need to be considered separately. The opportunity costs of the farmland would be relatively lower for landowners with lower income; therefore, they would be more likely to join the conservation program. On the other hand, landowners with greater farm size are more likely to have the advantage of "Economies of Scale", because the larger scale of land might lead to lower the average costs for conservation adoptions. For this type of landowners, the environmental benefits and landowner stewardship might be more important than the payment for them to join the conservation program. These indicate that an incentive payment scheme that targets farmers for compensation should have different foci and be in line with consideration of social equity. We add a caveat, however, that our sample had a relatively small share of low income landowners (annual income less than $25,000). Therefore, our estimates may not be precise enough for this income category landowners, and extra care should be taken when extrapolating WTA to low income regions.

Regarding socio-psychological characteristics, all the behavioral- attitudinal variables except for awareness of environmental issues showed statistical significance in predicting the participation in the incentive conservation program. As noted in Aldrich et al. (2007), the importance of including behavioral and attitudinal variables to evaluate preferences heterogeneity cannot be overemphasized. Specifically, the latent variable measuring past conservation experience, the appreciation of ecosystem services, and the sense of responsibility to watershed conservation all showed strong positive statistical effects on choosing the conservation program. However, simply being aware of the environmental problem did not impact landowners' decisions significantly. Similar ideas can be found in Olive (2014) in which the association between positive attitudes towards conservation programs is stronger over general knowledge or awareness.

Although most of the behavioral-attitudinal variables showed statistically significant effects in the MXL model, their roles in estimating the total willingness-to-pay are not vital. Based on the coefficients from Model 2, the mean TWTA is $395/acre for wetland, $10/acre for cover crops, and $102/acre for nutrient management. The estimates from Model 3 are $403/acre for wetland, $17/acre for cover crop, and $111/acre for nutrient management. By comparison, the TWTA estimates from Model 1 are significantly higher than Model 2 and Model 3, but the differences between Model 2 and Model 3 TWTA estimates were not statistically significant. The TWTA comparisons point towards an interesting argument related to non-market valuation, which is linked to heterogeneous costs estimation for environmental conservation programs. Contingent valuation methods such as DCE have long been criticized for overlooking the importance of socio-psychological factors in evaluation. From our study, however, behavioral-attitudinal characteristics are relevant in preference formation, but do not cause significant differences in estimating the TWTA values. In practice, socio-psychological information about landowners might not be available for most environmental agencies. In contrast, socio-demographic data are usually accessible for analysis and policy design. Our study provides evidence that DCE models with observed socio-demographic characteristics can still produce fairly comparable TWTA estimates even without adding unobservable psychological characteristics.

## *4.6 Conclusion*

This study applies a choice experiment to reveal preference heterogeneity of landowners for land conservation practices and compensation payment mechanisms in the region of Minnesota River Basin. Results from DCE show the important role of incentive payment in mobilizing the adoptions of wetland, cover crops and nutrient management practices on private land. On average, our findings suggest the total Willingness-to-Accept is around \$400/acre for wetland restoration, \$14/acre for cover crops, and \$106/acre for nutrient management. These values are fairly consistent with the incentive payment rates used by USDA Natural Resources Conservation Service. Among the observed sources of preference heterogeneity, we found that the annual income and farm size of the respondents, as well as the regional political leanings, monthly tax, and area of impaired water bodies all significantly affect the preference formation.

In terms of the heterogeneity in socio-psychological features, it was evident that the appreciation of ecosystem services, past conservation experience, and the sense of responsibility all significantly influenced landowners preference for conservation. As a way to gain support from landowners for conservation, encouraging outdoor activities and recreation deserves a particular attention. Based on our findings, appreciation of the beauty of nature and the benefits of ecosystem services works much better than the simple awareness of environmental problems in affecting the preferences to conservation programs compared to the status quo.

Results from this study confirmed the important roles of socio-psychological characteristics in studying preference heterogeneity. However, when evaluating the willingness-to-accept for conservation practices, our results show that only socio-demographics characteristics alone can still produce “sufficiently useful” estimates. Since data of the subjective perceptions or cognitive factors are not easily accessible for environmental agencies in real practice, we would suggest to focus more on collecting the objective demographic information for policy design and evaluation considering the constraint of resource limitation.

# Chapter 5

# CONCLUSIONS AND FUTURE PERSPECTIVES

## *5.1 Conclusions*

Incentive programs that encourage conservation management decisions are the backbone of strategies to sustain productive agricultural systems and environmental public goods. Past incentive programs have led to measurable localized benefits relative to a no-conservation practice counterfactual (USDA NRCS, 2003a,b,c). However, despite the edge of field gains, water quality within receiving lakes and river networks remains impaired in many locations and budget constraints limit the expansion of ongoing efforts to address these challenges (Shortle et al., 2012). A particular challenge to the cost-effective incentive designs and targeting is to account for the heterogeneity of both benefits and costs related to the conservation practices. Proper targeting requires crafting policies that reflect biophysically- and socially-driven spatial variation in the environmental benefits and private costs of alternative farm management practices. Herein, we have presented a framework that integrated the farm-scale management decisions and biophysical consequences into an optimization analysis to evaluate the cost-efficiency of the incentive designs in the presence of spatial heterogeneity and interdependency. Meanwhile, we conducted a stated preference survey of agricultural landowners to elicit farmers' preferences heterogeneity. The data we collected was used to explore the underlying socio-demographic and socio-psychological drivers of landowners' conservation decisions, and to develop the distributions of individual-level, county-level, and subbasin-level WTA costs for the management actions considered (wetland restoration, cover crops, nutrient management). Applied to the Minnesota River Basin, our research has produced the following main results:

1. We explored the utility of using simple heuristics (weighted benefit-to-cost ratios) in a

realistic optimization example where epistasis (i.e. spatial interdependence) is present via the "intelligent seeding" paradigm. Our results are the following. First, we show the existence of epistasis in the sediment reduction model by evaluating the solutions obtained from the simple weighted benefit-to-cost ratio ranking procedure. Second, we demonstrate that employing the benefit-to-cost ratio approach to generate "seeds" (starting points) for simulation-optimization produces marked improvements in the evolutionary algorithm performance. Finally, we provide a set of tradeoff results for the study watershed which can be resolved spatially (identifying the cost-effective mix and location of conservation actions in the watershed). The broader implication is that, while the "benefit per dollar" approach is largely obsolete by itself, it is still important as a part of optimization methodology and as a part of communicating the results from evolutionary algorithm iterations, which often have a "gray box" flavor, whereby the simulation-optimization results are directly derived and compared to well-known and well-understood benefit-to-cost heuristics.

2. Under the framework of Theory of Planned Behavior (TPB) and Diffusion of Innovation (DoI), we applied factor analysis and regression modeling to explore the underlying socio-psychological drivers of landowners' intentions for BMPs adoption. According to our results, both favorable and unfavorable attitudes, awareness of environmental problems, and appreciation of ecosystem services all significantly influence landowners' adoption intentions for wetland restoration, cover crop, and nutrient management. The past-experience attribute shows significant positive influences on intentions for cover crops and nutrient management, while the impacts from normative social pressures are negative.

3. We employed cluster analysis to investigate the nuances of both socio-psychological and socio-demographic characteristics among landowners. We divided landowners into three groups: environmental-friendly landowners, economic-leaning landowners, and adoption-averse landowners. The environmental-friendly landowners are statistically

different from the other two clusters in each TPB & DoI construct. Their intentions to three BMPs adopting are also significantly higher. Demographically, they are relatively younger and have higher education. Both economic-leaning landowners and adoption-averse landowners care less about conservation and have lower intentions to BMPs adopting. However, the economic-leaning landowners have higher scores regarding concerns, awareness, and favorable attitudes to BMPs, while they have relatively low scores in behavioral control and past-experience. The adoption-averse cluster is the opposite of the environmental-friendly cluster in almost every TBI & DoI construct, except the past-experience dimension. The adoption-averse landowners have a relatively high score in the past-experience factor. However, previous experience about the conservation programs may negatively affect their intentions of adopting.

4. We have adopted the Stated Preference survey and dichotomous discrete choice experiments to reveal landowners' preference heterogeneity for land conservation practices and compensation payment mechanisms. Results show the importance of incentive payment in mobilizing the adoptions of conservation practices on private land. We have simulated the distributions of individual-level WTA costs for three management actions considered. We also scaled the WTA estimates up to the county-level and subbasin-level so that they can be reasonably coupled with a regional-specific biophysical model for benefit-cost analysis.

   In terms of the sources of preference heterogeneity, we have found a set of socio-demographic characteristics such as annual income and farm size of the respondents, as well as the regional political leanings, monthly tax, and area of impaired water bodies all significantly affect the preference formation. Meanwhile, it is evident that behavioral-attitudinal attributes, such as appreciation of ecosystem services, past conservation experience, and the sense of responsibility all significantly influenced landowners' preference for conservation.

## *5.2 Future Perspectives*

The methodologies and empirical studies presented in this research provide insights into incentive policy designs for cost-efficiently reducing agricultural nonpoint source pollution. Based on our work, there are several exciting topics worth further investigation.

- *Cost-effectiveness predictions and priority zones classification.* For the sake of policy design and generalizability, it would be important to know which are the key model inputs that determine management cost-effectiveness so that policies can be based on these biophysical characteristics, rather than a particular set of model outputs. Our modeling results about biophysical change, economic costs, and potential public benefits can be the inputs for machine learning models that can predict the cost effectiveness (benefit per $ of cost) of given alternative practices. With the predictions, one can then classify the land unit into distinct cost-effectiveness classes, or "priority zones".

- *Policy simulation and comparison.* With our integrated natural-human system modeling, one can simulate farmers' management responses to incentive policy, biophysical processes, and consequences for public and private objectives. Moreover, it will be interesting to compare alternative incentives and targeting strategies in terms of cost-effectiveness relative to each other and to the first-best benchmark. Different incentive policy options may include but are not limited to payments based on practice and payments based on performance. The incentive can then be targeted either by geography (e.g. sub-watershed) or biophysical characteristics (e.g. slope or soil type) in a policy optimization framework to determine approaches that bring the outcomes of the second-best mechanisms closer to the hypothetical first-best solutions.

- *Optimization for robust incentives.* Uncertainty will enter into simulation models from a variety of sources, such as key parameters in the biophysical models, the cost assumptions, and exogenous stochastic factors such as the weather and agricultural commodity prices. The uncertainty can affect an incentive program's outcomes, either in the simulated results or resulting in differences between simulations and the actual outcome. Therefore, we suggest evaluating the sensitivity of the integrated model and then identifying incentive programs most likely to produce desirable outcomes despite the uncertainty. Modeling frameworks such as Multi-Objective Robust Decision-Making (Kasprzyk et al., 2013) would be useful tools to facilitate finding optimal solutions for complex, multi-objective problems under uncertainty .

## *5.3 Contributions*

Environmental science is a highly interdisciplinary academic field that studies environmental issues through a pluralistic view. In this project, analytical methods and techniques in mathematical statistics, economics, civil engineering, and computer programming are integrated to improve the understanding of how biophysical, economic, and social processes operate within a watershed. The framework of defining, solving, and evaluating the integrated model is an empirical example of the interdisciplinary study of the complex natural-human system.

Although we apply the modeling framework to the Minnesota River Basin, it is conceptually transferable to other basins across the nation or globe. This research is anticipated to advance scientific understanding of the relative roles of cost-efficient watershed management towards controlling agricultural nonpoint source pollution, which could help with generalizing knowledge beyond place-specific results. It will also advance land use policy and decision making research by demonstrating that effectively tackling spatial and preference heterogeneity can lead to more nimble analysis tools for better planning.

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# Appendix A

# COMPUTATIONAL EXPERIMENTS FOR EPISTASIS IN OPTIMIZATION

## *A.1 The proof of wBCR ranking as a Pareto non-dominant solution*

Re-write the multiobjective optimization problem as:

$$\max_{x \in \mathcal{X}} f(x) = \max f(f_b(x), f_g(x), -f_c(x)) = \max(\sum_{i=1}^{n} b_i x_i, \sum_{i=1}^{n} g_i x_i, -\sum_{i=1}^{n} c_i x_i) \tag{A.1}$$

Suppose there is another decision vector $\hat{x}_m \in \mathcal{X}$ with $m$ elements, that dominates $x_k$, then we should have (without loss of generality)

$$\begin{cases} f_b(x_k) \leq f_b(\hat{x}_m) \Longrightarrow \sum_{i=1}^{k} b_i x_{ki} \leq \sum_{i=1}^{m} b_i \hat{x}_{mi} \\ f_g(x_k) \leq f_g(\hat{x}_m) \Longrightarrow \sum_{i=1}^{k} g_i x_{ki} \leq \sum_{i=1}^{m} g_i \hat{x}_{mi} \\ -f_c(x_k) < -f_c(\hat{x}_m) \Longrightarrow \sum_{i=1}^{k} c_i x_{ki} > \sum_{i=1}^{m} c_i \hat{x}_{mi} \\ f(x_k) \neq f(\hat{x}_m) \end{cases} \Longrightarrow \begin{cases} \sum_{i=1}^{k} \frac{b_i}{c_i} x_{ki} < \sum_{i=1}^{m} \frac{b_i}{c_i} \hat{x}_{mi} \\ \sum_{i=1}^{k} \frac{g_i}{c_i} x_{ki} < \sum_{i=1}^{m} \frac{g_i}{c_i} \hat{x}_{mi} \end{cases}$$

which indicates that with $\lambda \in \big[0, 1\big]$ we should have

$$\lambda \sum_{i=1}^{k} \frac{b_i}{c_i} x_{ki} + (1-\lambda) \sum_{i=1}^{k} \frac{g_i}{c_i} x_{ki} < \lambda \sum_{i=1}^{m} \frac{b_i}{c_i} \hat{x}_{mi} + (1-\lambda) \sum_{i=1}^{m} \frac{g_i}{c_i} \hat{x}_{mi} \tag{A.2}$$

If we use $r_i$ to represent the weighted benefit-to-cost ratios, then equation A.2 can be written as:

$$\sum_{i=1}^{k} r_i(x_{ki}) < \sum_{i=1}^{m} r_i(\hat{x}_{mi}) \tag{A.3}$$

**Case 1:** $m = k$

When $\hat{x}_m$ contains the same number of elements as $x_k$, equation A.3 **contradicts** the fact that

$x_k : \left\{x_{r(1)}, x_{r(2)}, ..., x_{r(k)}, ..., x_{r(n)}\right\} = \{1, 1, ..., 1, 0, ..., 0\}$ are sorted in a descending order by the value of $\lambda\frac{b_i}{c_i} + (1-\lambda)\frac{g_i}{c_i}$, which indicates that

$$\text{argmax}\left[\lambda \sum_{i=1}^{n} \frac{b_i}{c_i} x_i + (1-\lambda)\sum_{i=1}^{n} \frac{g_i}{c_i} x_i\right] = \text{argmax}\left[\sum_{i=1}^{n} r_i(x_i)\right] = x_k \tag{A.4}$$

which means

$$\sum_{i=1}^{k} r_i(x_{ki}) > \sum_{i=1}^{m} r_i(\hat{x}_{mi}) \tag{A.5}$$

Therefore, it must be that no other decision vector Pareto-dominates $x_k$.

**Case 2:** $m < k$

When $\hat{x}_m$ contains less elements then $x_k$, according to equation A.3, we have

$$\sum_{i=1}^{k} r_i(x_{ki}) + \sum_{i=k+1}^{m} r_i(x_{ki}) < \sum_{i=1}^{m} r_i(\hat{x}_{mi}) \tag{A.6}$$

But from equation A.5, we know that $\sum_{i=1}^{k} r_i(x_{ki}) > \sum_{i=1}^{m} r_i(\hat{x}_{mi})$.

Therefore, equation A.6 is impossible.

**Case 3:** $m > k$

When $\hat{x}_m$ contains more elements then $x_k$, equation A.3 becomes

$$\sum_{i=1}^{k} r_i(x_{ki}) < \sum_{i=1}^{k} r_i(\hat{x}_{mi}) + \sum_{i=k+1}^{m} r_i(\hat{x}_{mi}) \tag{A.7}$$

By itself, A.7 is possible, yet the following would also have to hold:

$$\sum_{i=1}^{k} c_i(x_{ki}) > \sum_{i=1}^{k} c_i(\hat{x}_{mi}) + \sum_{i=k+1}^{m} c_i(\hat{x}_{mi}) \tag{A.8}$$

However, the proof in case 1 indicates that $\sum_{i=1}^{k} c_i(x_{ki}) \leq \sum_{i=1}^{k} c_i(\hat{x}_{mi})$, which alone makes the equation A.8 impossible.

## *A.2 MOSM modules*

Table A.1: Various management alternatives are grouped into Management Option (MO) types according to sediment sources and mechanisms of sediment loading reduction

| MO Types | Description | Location of implementation | Example management practices |
|---|---|---|---|
| Tillage MO (TLMO) | Crop production and tillage management | Field | Conservation tillage, reduced tillage, conventional tillage |
| Agricultural Field MO (AFMO) | Field erosion management | Field | Grassed water ways |
| Water Conservation MO (WCMO) | Field water storage to attenuate peak river discharge | Field | Water Retention ponds, wetland restoration |
| In-channel Water Conservation MO (ICMO) | In-channel water storage to attenuate peak river discharge | Channel | Temporary water storage in channel |
| Buffer MO (BFMO) | Vegetation planting near channel | Field near channel | Buffer strips |
| Ravine MO (RAMO) | Ravine tip stabilization to reduce branch growth | Ravines | Ravine tip stabilization |
| Near Channel MO (NCMO) | Bluff erosion management | Bluffs | Bluff stabilization, toe protection |

## *A.3 Wildlife model*

The model for estimating duck hatchlings (H) affected by wetland restoration options (WCMO) is a function of the nesting pairs (NP), nest success (NS), re-nesting propensity (NI), and clutch size (CS) (Hansen et al., 2015).

$$H = NP \times NS \times NI \times CS \tag{A.9}$$

An additional factor, should one be focused on adult duck numbers, would be the one associated with survival from hatchlings to adult ducks (referred as the reproductive success). It contains two aspects: the survival from hatching to fledging and the post fledging survival to recruitment, which is often measured by the number of offspring that enter the breeding population (Dzus and Clark, 1998). We do not have good estimates of reproductive success for all the duck species in our study, but we note that for black ducks, according to the results from Ringelman and Longcore (1982), young ducklings had a survival rate of 0.6073, which was significantly lower than the 0.6988 rate for older ducklings. The total brood survival was estimated at 81% (Ringelman and Longcore, 1982). Hatchling numbers for other species could then can be easily adjusted, given the appropriate estimate of reproductive success.

Using existing nesting pair and nest success models, as well as field survey data (Reynolds et al., 2006; Mayfield, 1975; Reynolds et al., 2001; Baldassarre, 2014) allows us to generate estimates of these parameters for the five duck species (mallard, gadwall, blue-winged teal, northern pintail, and northern shoveler) in the Le Sueur River Watershed.

The nesting pairs (NP) represents the number of breeding ducks in a wetland, considering the effects of the wet area and geographical locations. Using the "Duck-Pair Regression Model" (Reynolds et al., 2006), we generate the output of NP for each WCMO:

$$\mathrm{NP}_i = a_1 w_i + a_2\sqrt{w_i} + a_3 w_i\sqrt{w_i} + a_4\sqrt{w_i}x_i + a_5\sqrt{w_i}y_i + a_6\sqrt{w_i}x_i y_i \tag{A.10}$$

where $a_1$, $a_2$, $a_3$, $a_4$,$a_5$, $a_6$ are species specific coefficients (Reynolds et al., 2006) and $w_i$ is the wet area of each WCMO[1]. $x_i$ and $y_i$ are the Universal Transverse Mercator (UTM) coordinates, measuring the longitude and latitude of the WCMO central point. The wet area $w_i$ is estimated from:

[1]Reynolds et al. (2006) estimated the wet area for four wetland types: temporary, seasonal, semi-permanent, and Lake. In our case, we specified our WCMOs as the semi-permanent wetland.

$$w_i = s_i\Big[e^{b_0+b_1 ln(x_i)+b_2 ln(y_i)+b_3 ln(x_i) ln(y_i)+b_4 ln(\text{BASINSIZE})} - 0.5\Big] \tag{A.11}$$

where $b_0$, $b_1$, $b_2$, $b_3$, $b_4$ are coefficients estimated by Reynolds et al. (2006), $s_i$ is the area of individual WCMO and BASINSIZE is the aggregated areas of WCMOs.

The nest success (NS) is the egg survival probability during the amount of time each nest is under observation (Mayfield, 1975), and is a primary driver of duck population maintenance (Hoekman et al., 2002). To estimate NS, we first calculate the daily survival rate (DSR) by applying a spatially explicit model from Reynolds et al. (2001). It accounts for the positive effects of the grassland area surrounding the wetland candidates:

$$\text{DSR}_i = c_0 + c_1(\text{PGRASS}_i \times 10^{-2}) + c_2(x_i \times 10^{-5}) + c_3(y_i \times 10^{-5}) + c_4(x_i \times y_i \times 10^{-12}) \tag{A.12}$$

where $c_0$ is species specific, and $c_1$, $c_2$, $c_3$, $c_4$ are coefficients estimated by Reynolds et al. (2001). PGRASS$_i$, the percent grass, is the share of grass cover within a one-mile radius of the centroid point of each wetland candidate. Using ArcGIS buffer tool with the local land cover data from Thematic Mapper satellite imagery, we did spatial search and calculated the percent grass within the surrounding one-mile radius of each wetland candidate.

The probability of successive events is then the DSR estimate of each species to the power of the number of nest-exposure days:

$$\text{NS}_i = \text{DSR}_i^d \tag{A.13}$$

where $d$ take values from 32 to 35 days (Baldassarre, 2014).

The NI for each duck species is treated as a constant and is taken from from Baldassarre (2014): mallard = 100%, gadwall = 82%, blue teal = 55%, northern shoveler = 75%, northern pintail = 55% (Hansen et al., 2015). Finally, the average clutch size (CS) also varies by species and is taken from Hansen et al. (2015): mallard=8.4, gadwall=9.9, blue teal=10.2, northern shoveler =7.1, and northern pintail = 9.9.

### A.4 Cost assumptions

For the cost of agricultural land conversion (relevant for AFMO, BFMO, and WCMO options), we use area-specific real options estimates reported in Schroder et al. (2018). The land conversion costs are estimated from the real option analysis at the county level which assumes that the uncertainty in agricultural profit translates into a higher critical payment which would be required to induce farmers to permanently switch away from crop production. For payments exceeding such critical payments $P^*$, permanent conversion away from agricultural production is assumed to be preferred by landowners. Note that $P^*$ are higher than $P^{NPV}$ because they reflect the real option value.

Table A.2: Land conversion costs

| County | $P^{NPV}$($/acre) | $P^*$($/acre) |
|---|---|---|
| Blue Earth | 282 | 312 |
| Faribault | 369 | 375 |
| Freeborn | 433 | 440 |
| Steele | 281 | 307 |
| Waseca | 358 | 364 |

For the installation and maintenance costs of the remaining MOs, we used the estimates reported in the Management Option Simulation Model Computational Module Handbook(Cho et al., 2017).

Table A.3: Number of candidate options and their installation and maintenance costs

| Management options (MOs) | Number of candidate sites | Installation Costs($/acre) | Maintenance Costs($/acre) |
|---|---|---|---|
| AFMO | 2,119 | 3,200 | 64 |
| BFMO | 517 | 1,000 | 45 |
| WCMO | 7,874 | 3,000 | 574 |
| ICMO | 537 | 250 | 1.4 |
| RAMO | 106 | 6,000 | 35 |
| NCMO | 1,112 | 200 | 0.7 |

## A.5 Pareto-frontiers estimated using EA

Table A.4: EA Pareto-frontiers

| Frontier | Number of individuals in the final frontier | Number of generations (iterations) to convergence (consolidation ratio of 0.99) | Optimization log name and location |
|---|---|---|---|
| $\mathcal{F}_0$ – no seeding | 1,342 | 15,995 | MOSM 2018-04-30 1248 SPEAMO `https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi%3A10.7910%2FDVN%2FQPESTS` |
| $\mathcal{F}_{unif}$ – seeding with uniform application of all MOs, plus a zero cost baseline and an "everything, everywhere" scenario | 4,406 | 1,576 | MOSM 2018-04-30 2110 `https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi%3A10.7910%2FDVN%2FLT7GD1` |
| $\mathcal{F}_{unif+wBCR}$ — seeds in the $\mathcal{F}_{unif}$ and wBCR seeds | 2,369 | 216 | MOSM 2018-04-30 1610 `https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi%3A10.7910%2FDVN%2FLFSSOZ` |

## A.6 Epistasis illustration

*Conceptual model of routing*

The conceptual source of epistasis in our sediment model is hydrologic interdependence of water-storing features along hydrologic flow-paths in the watershed, especially as it manifests itself in reductions in peak flows (main physical driver of near-channel sediment in our model). As an example of how sequential water reservoirs reduce (and delay) peak flows, we include a "classic derivation" (in the words of Hansen et al. (2003)) in hydrology which shows that the effect of placing a reservoir in a flow-path depends on presence of other reservoirs upstream or downstream

In MOSM, the routing algorithm simulates the changes in the time and magnitude of peak river discharge as a result of the change of water storage by implementing WCMO and ICMO in the 30 hydropathic subbasins of the watershed. The first part of routing is simulated by the "level pool routing" method, which estimates the effects of water storage on subbasin water yield; whereas the second part applies the Muskingum-Cunge method to route the subbasin water yield downstream.

Theoretically, both the level pool routing and Muskingum-Cunge routing are governed by a lumped form of continuity equation and a functional storage-discharge relationship. The continuity equation is:

$$Q_{in} - Q_{out} = \frac{ds}{dt} \tag{A.14}$$

where $s$ is the water storage volume in any given reservoir, $Q_{in}$ is the inflow supplied by the next-most upstream reservoir, $Q_{out}$ is the discharge, and $\frac{ds}{dt}$ is the rate of changes of storage volume in the reservoir.

To obtain an analytical solution for the $n^{th}$ reservoir, we follow Hansen et al. (2003) to model the level pool routing for a cascade of linear reservoirs. The relationship between storage and discharge for the cascade system is defined by a linear coefficient $K$:

$$s = KQ_{out} \tag{A.15}$$

Combine eq.A.14 and eq.A.15 to obtain the $n^{th}$ hydrograph for the successive linear reservoirs in a cascade:

$$Q_{in} - Q_{out} = K\frac{dQ_{out}}{dt} \tag{A.16}$$

For the first reservoir, assuming it has an instantaneous volume in it, so $Q_{in} = 0$ after $t = 0$:

$$-Q_{out} = \left.\frac{ds}{dt}\right|_{t>0} \tag{A.17}$$

Substituting eq.A.15 into eq. A.17 gives

$$\begin{aligned} -Q_{out} &= K\left.\frac{dQ_{out}}{dt}\right|_{t>0} \Rightarrow \\ \frac{Q_{out}}{dQ_{out}} &= -K\left.\frac{1}{dt}\right|_{t>0} \end{aligned} \tag{A.18}$$

Integrating eq.A.18 from $t = 0^+$ to time $t$:

$$\int_{0^+}^{t} \frac{1}{Q_{out}} dQ_{out} = -\frac{1}{K}\int_{0^+}^{t} dt \Rightarrow ln(\frac{Q_{out}}{Q_{out}\big|_{t=0^+}}) = \frac{-t}{K}$$
$$\Rightarrow \frac{Q_{out}}{Q_{out}\big|_{t=0^+}} = \exp(-\frac{t}{K}) \tag{A.19}$$

From eq.A.15, $Q_{out} = \frac{s}{K}$, so it is also true that

$$Q_{out}\big|_{t=0^+} = \frac{s_0}{K} \tag{A.20}$$

Substituting eq.A.20 into eq.A.19 gives:

$$Q_{out} = \frac{s_0}{K}\exp(\frac{-t}{K}) \tag{A.21}$$

Integrating eq.A.21 gives the volume drained after a given elapsed time for reservoir 1:

$$V = \int Q_{out} dt = \int_0^t \frac{s_0}{K}\exp(\frac{-t}{K})dt$$

Denoting $\kappa$ as $\frac{s_0}{K}$ and $\beta = \frac{1}{K}$:

$$V = \int_0^t \kappa \exp(-\beta t)dt = -\frac{\kappa}{\beta}\exp(-\beta t)\Big|_0^t = -\frac{\kappa}{\beta}\exp(-\beta t) + \frac{\kappa}{\beta} \tag{A.22}$$

Re-substituting the definitions:

$$V = s_0\left[1 - \exp(-\frac{1}{K}t)\right] \tag{A.23}$$

Now, route this exponentially-decaying flow coming out of reservoir 1 (described by eq.A.21) through reservoir 2. Substituting eq.A.21 into eq.A.16 as the new $Q_{in}$:

$$\frac{s_0}{K}\exp(-\frac{t}{K}) - Q_{out} = K\frac{dQ_{out}}{dt} \tag{A.24}$$

Solving the differential equation using an integrating factor[2] gives:

$$Q_{out} = \frac{s_0}{K} t \exp(-\frac{t}{K}) \tag{A.25}$$

In the limit (3rd reservoir and beyond), repeating the entire procedure n times gives the following equation for the general outflow $Q$:

$$Q = \frac{1}{(n-1)!K^n} t^{n-1} \exp(-\frac{t}{K}) \tag{A.26}$$

One can see that with the initial storage $S_0 = 1$, the shape of the hydrographs closely matches the two-parameter Gamma function:

$$Q = \frac{1}{\Gamma(n)K^n} t^{n-1} \exp(-\frac{t}{K}) \tag{A.27}$$

The same function with an initial volume $S_0$ is then:

$$Q = \frac{s_0}{\Gamma(n)K^n} t^{n-1} \exp(-\frac{t}{K}) \tag{A.28}$$

The PMF of Gamma distribution (associated with eq.A.27) is more commonly written as:

$$f(x;\alpha,\beta) = \frac{1}{\Gamma(\alpha)\beta^\alpha} t^{\alpha-1} \exp(-\frac{x}{\beta}) \tag{A.29}$$

The Gamma distribution can conveniently be used to synthesize an entire hydrograph if the peak discharge and its associated time $t$ are known. Comparing eq.A.28 and eq.A.29, it's obvious that $t = x, n = \alpha, k = \beta$.

Apply eq.A.28 to the peak flow rate $Q_{max}$ and its associated time $t_{Q_{max}}$ :

[2]An example about integrating factor method can be found at `http://weber.itn.liu.se/~krzma/DS2017/Integrating%20factor%20method.pdf`

$$Q_{max} = \frac{s_0}{\Gamma(n)K^n} t_{Q_{max}}^{n-1} \exp(-\frac{t_{Q_{max}}}{K}) \tag{A.30}$$

Dividing eq.A.28 by eq.A.30:

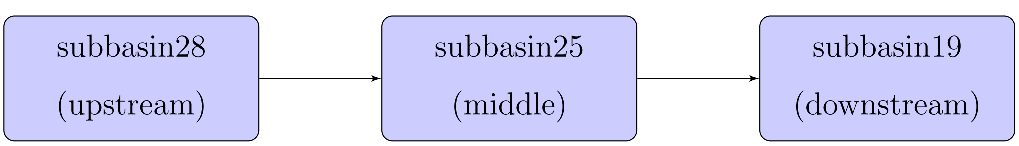
$$\frac{Q}{Q_{max}} = (\frac{t}{t_{Q_{max}}})^{n-1} \exp(\frac{t_{Q_{max}} - t}{K}) \tag{A.31}$$

From the derivation process, one can see that the shape of the gamma distribution of the hydrographs is dependent on the number of reservoirs in the cascade system, indicating that the effect of placing a linear reservoir on discharge anywhere in the cascade of level pools is dependent on the presence or absence of other reservoirs in the cascade.

As we mentioned above, in our MOSM model, the routing processes that determine the water discharge serve as the fundamental mechanisms for driving sediment loadings. The epistasis in sediment reduction, therefore, is the manifestation of the interdependent effects on hydrographs from management sites in subbasins of the watershed.

*Experiment Design*

To provide a simulation example of the magnitude of the epistasis, we demonstrate how hydrologic relationships affect sediment reductions in a simple upstream/mid-watershed/downstream simulation example. Since our individual water-storing management options are quite small, we conduct a full combinatorial experiment of activating all water-storing features in the 3 subbasins lying in a flow-path.




The experiment results show that, for example, if one were to fully adopt all water-storing features in an upstream and a downstream subbasin and ignore their interdependence and simply add up the estimated downstream sediment reductions, a policymaker would be over-

Table A.5: Number of potential water-storing management site

| | Subbasin28 | Subbasin25 | Subbasin19 |
|---|---|---|---|
| WCMOs | 663 | 268 | 216 |
| ICMOs | 14 | 23 | 1 |
| Total | 677 | 291 | 217 |

Table A.6: Experiment for calculating epistasis magnitude

| | Subbasin28 | Subbasin25 | Subbasin19 | Sediment Reduction | Across subbasin interactions | | |
|---|---|---|---|---|---|---|---|
| | Upstream | Middle | Downstream | MOSM imulation | Subbasins involved | Interaction magnitude (absolute) | Interaction magnitude (relative) |
| Scenario 1 | 0 | 0 | 0 | 0 | none | - | - |
| Scenario 2 | 1 | 0 | 0 | 14243.47 | upstream | - | - |
| Scenario 3 | 0 | 1 | 0 | 4495.98 | middle | - | - |
| Scenario 4 | 0 | 0 | 1 | 5308.3 | downstream | - | - |
| Scenario 5 | 1 | 1 | 0 | 17936.97 | upstream/middle | -3872.73 | 22% |
| Scenario 6 | 1 | 0 | 1 | 18650.58 | upstream/downstream | -3656.08 | 20% |
| Scenario 7 | 0 | 1 | 1 | 9534.08 | middle/downstream | -1313.25 | 14% |
| Scenario 8 | 1 | 1 | 1 | 22067.28 | upstream/middle/downstream | -5414.56 | 25% |

estimating sediment reductions by as much as 20%. Note that these effects are distinct from the known "delivery ratio" considerations.

## *A.7 Robust solutions from wBCRs*

While a formal incorporation of risk or robust decision-making is beyond the scope of the current manuscript, we conducted a simple yet hopefully useful exercise to address some of these issues about identifying key subbasins in the watershed in a more robust manner. In particular, since our procedure of ranking decision-making units based on weighted benefit-cost ratios (wBCR) is nearly efficient in terms of finding cost-effective locations, we can directly go to the actual values of location-specific wBCRs and look at them in a cardinal, as opposed to the purely ordinal, way. Specifically, we compute the nearest-neighbor distance in terms of a wBCR across units ranked in descending order across their wBCRs. This approach is related to a PRIM (Patient Rule Induction Method) (Hadka et al., 2015) approach to robust decision making, and essentially measures the relative magnitude of error in the ratio of estimated environmental benefits to costs which maintains the prioritization ranking of decision-making units in the LeSueur River basin. This kind of analysis allows the policymakers to identify in space the locations which are likely to remain cost-efficient even if the optimization assumptions represented by the biophysical and the economic model do not hold.

In our study, solutions from weighted benefit-to-cost ratio rankings serve as starting points form EA. And we have shown that it not only improves the performance of EA but 90% of the solutions from wBCR rankings survived after the EA iterations. For the robustness analysis, we use the difference of the wBCR ratios (referred as "wBCR distances") between the adjacent positions in the ranked sequences as the metrics that calibrate the resistance of the management site. The greater wBCR distance, the more robust the candidate site is.

We then display the robustness metrics by the choropleth maps of the wBCR distances. For scenarios $\lambda = 1$ (only focus on sediment reduction) and $\lambda = 0.5$ (equal weight on both sediment reduction and duck production), one can see that subbasins closer to the outlets or lie along the stream paths have greater wBCR distances than others, indicating these locations might be more robust in the benefit-to-cost ratio ranking process. For $\lambda = 0$ (only focus on duck production), however, the spatial pattern is not as clear as the ones in the previous two choropleth maps.

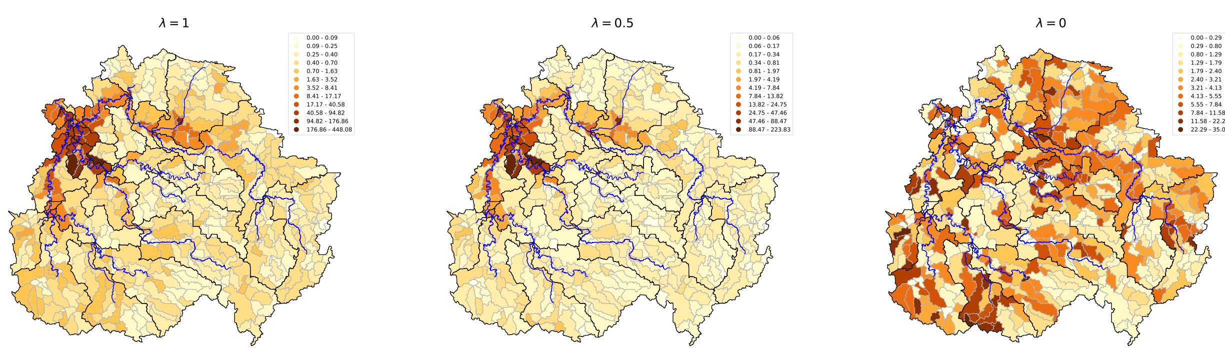



Figure A.1: Spatial pattern of wBCR distances.

To further test the idea that the wBCR robustness might be related to locations relative

Table A.7: Correlations between the wBCR robustness and spatial distances

| | | Estimate | Std. Error | t value | Pr(>\|t\|) |
|---|---|---|---|---|---|
| $\lambda = 1$ | (Intercept) | 11.4710 | 2.7481 | 4.17 | 0.0000*** |
| | StreamDist | -0.0004 | 0.0001 | -3.72 | 0.0002*** |
| | OutletDist | -0.0000 | 0.0001 | -0.19 | 0.8459 |
| $\lambda = 0.5$ | (Intercept) | 5.7269 | 1.3736 | 4.17 | 0.0000*** |
| | StreamDist | -0.0002 | 0.0000 | -3.72 | 0.0002*** |
| | OutletDist | -0.0000 | 0.0000 | -0.19 | 0.8508 |
| $\lambda = 0$ | (Intercept) | 0.0003 | 0.0000 | 6.01 | 0.0000*** |
| | StreamDist | -0.0000 | 0.0000 | -1.90 | 0.0580* |
| | OutletDist | 0.0000 | 0.0000 | 1.53 | 0.1276 |

***, **,* : Significance at 1%, 5%, 10% level.

to the stream paths and outlet, we calculated the nearest distances to streams and outlet as the explanatory variables and fitted a linear regression to estimate the parameters.

For $\lambda = 1$ and $\lambda = 0.5$, we find a significant negative correlation (significance level of 0.01) between the wBCR robustness and the distance to streams. For $\lambda = 0$, the correlation is much lower (significance level of 0.1). In terms of the parameter of distance to the outlet, in all of the three scenarios, the estimates are not significant.

# Appendix B

# MINNESOTA RIVER BASIN AGRICULTURAL LANDOWNER SURVEY

## *B.1 Invitation Letter*

**Dear ⟨SALUTATION⟩,**

Researchers at the University of Washington, in collaboration with University of Minnesota partners, are seeking your opinions regarding water quality improvements in the Minnesota River Basin. The University of Washington's Internal Review Board (Approval #00003970) has reviewed our study. Your individual responses will be kept strictly confidential.

### *A bit of background*

In 1992, Governor Arnie Carlson issued a challenge to make the Minnesota River fishable and swimmable by 2002. Twenty-five years after this announcement, more than 40 percent of Minnesota's waters are still polluted. Harmful aquatic invasive species have infested more than 550 lakes statewide, and the clean drinking water systems are in serious disrepair.

In 2017, Governor Mark Dayton announced a new **"25 by 25"** water quality goal, aiming to improve water quality in Minnesota by 25 percent by 2025. Without additional action, the quality of Minnesota's waters is expected to improve only 6 to 8 percent by 2034.

As a local resident and landowner, your attitudes and actions are especially important for achieving this goal. Understanding what you think about different land management options for your land and what is most important to you for the Minnesota River Basin as a whole will help in designing effective and fair local strategies.

The state of Minnesota is committing funds to support voluntary landowner actions for water quality improvements. Your responses will help shape the direction of these programs and the set of land management practices for which payments may be offered.

**Please participate in our study by typing** `http://bit.do/2q1927` **in your Web browser or by scanning the QR code below with a smartphone or a tablet.**

The survey is around 10-15 minutes in length. We really appreciate for your participation! Please accept the enclosed $2 bill as a taken of our gratitude.

If you have any questions, please don't hesitate to contact me directly at `rabotyag@uw.edu` or 206-865-3159. If you would like a paper version of the questionnaire, please let us know and we will send you one. Your privacy is important to us: we have obtained your contact information from a local list of agricultural businesses, but if you do not want to receive any further communication from us regarding this study, please let us know.

We know your time is valuable but your input is very important to us, and we hope you find the survey engaging and maybe even fun!

Thank you!

### *B.2 Postcard Reminder*

**Dear ⟨SALUTATION⟩,**

We recently sent you an invitation, along with a $2 token of our appreciation for your input, to participate in an important survey about water quality issues in the Minnesota River Basin. We have not yet heard back from you.

Please participate in our study by going to `http://bit.do/2q1927`, or scanning the QR code below.

We really want to hear from you!

### *B.3 Reminder Letter*

**Dear ⟨SALUTATION⟩,**

Four weeks ago we sent you a survey invitation letter, followed by a poster card reminder, seeking your opinions about land conservation practices and potential payment mechanisms for water quality protection in Minnesota River Basin. If you have already submitted your survey, thank you for your valuable input. If not, **please participate in our study by typing** `http://bit.do/2q1927` in your Web browser or by scanning the **QR** code below with a smartphone or a tablet. Or please take the **paper version of the survey**, and use the envelope enclosed to send it back.

We have extended the due date because your particular responses are vital in helping us design the optimal and adaptable watershed protect strategies for each of Minnesota's eight local watershed regions and communities to employ. If you have any questions, please don't hesitate to contact me directly at `rabotyag@uw.edu` or 206-865-3159.

We know your time is valuable but your input is very important to us, and we hope you find the survey engaging and maybe even fun! Thank you!

### *B.4 Final Postcard Reminder*

**Dear ⟨SALUTATION⟩,**

We are still seeking your opinions about land conservation practices and potential payment mechanisms for water quality protection in the Minnesota River Basin. If you have already submitted your survey, thank you for your valuable input. If not, please complete this survey online at `http://bit.do/2q1927`, or by returning a paper survey copy we sent recently, or call us 206-685-3159 for a replacement copy.

As the local resident and landowner, your attitudes and actions are especially important for the water protection process of the Minnesota State. We have extended the due date because your particular responses are vital in helping us design the optimal and adaptable watershed protection strategies for Minnesota's local communities to employ. If you have any questions, please contact us at `rabotyag@uw.edu` or `langzx@uw.edu`.

### *B.5 Paper Version of The Survey*

# Minnesota River Basin Agricultural Landowner Survey

## Part I. Tell us about yourself

*It is important that we first understand your particular land ownership situation and your concerns about water quality in Minnesota River Basin.*

1. **County of residence**: ______________________
2. **How many total acres of agricultural land do you own**: I own________ acres agricultural land.
3. **In which county is all or most of your land located?**: ______________________
4. **Is the majority of land you own used for growing crops?**
   - ☐ Yes, and I am in charge of a day to day farm operation.
   - ☐ Yes, and someone else is in charge of a day to day farm operation.
   - ☐ No, majority of my land is not currently used for crop production.
5. **Thinking about your land in the past 5 years, have you personally made management decisions for the following? (Check all that apply)**
   - ☐ Selection of crop varieties and rotations.
   - ☐ Selection of fertilizers/chemicals and cultivation practices.
   - ☐ Marketing and crop insurance.
   - ☐ Adoption of one-season conservation practices (conservation tillage, etc.).
   - ☐ Adoption of long-term conservation practices (grass waterways, etc.).
   - ☐ Government commodity programs.
   - ☐ Government conservation programs (CRP, EQIP, etc.).
6. **Currently, is any of your land (Check all that apply)**
   - ☐ Enrolled in Conservation Reserve Program (CRP).
   - ☐ Enrolled in Environmental Quality Incentives Program (EQIP).
   - ☐ Under non-Federally funded conservation easement.
   - ☐ Enrolled in Conservation Stewardship Program (CSP), Agricultural Conservation Easement Program (ACEP), or other government conservation programs.
7. **Currently, have you adopted any of the following conservation practices?(Check all that apply)**
   - ☐ Grassed waterways ☐ Minimum/no-till ☐ Riparian buffers ☐ Retention ponds
   - ☐ Other ______________________
8. **In the past five years, approximately what percent of your household income has come from farming?**
   - ☐ 0% ☐ 1-25% ☐ 25-50% ☐ 50-75% ☐ 75-100%
9. **What is the primary crop/crop rotation on the land that you own?**
   - ☐ Corn/Bean (All Conventional till) ☐ Corn/Corn/Bean (All conventional till)
   - ☐ Corn/Bean(All No-till) ☐ Corn/Corn/Bean(Minimum-till corn, No-till bean)
   - ☐ Wheat ☐ Sugarcane and Sugar Beets
   - ☐ Continuous Corn (any tillage system) ☐ Alfalfa/other hay
   - ☐ Conservation Reserve Program (CRP) ☐ Other ______________________

**10. Which of the following best describes your work in 2017?**

- ☐ Full-time farm work on land owned by me or rented from others
- ☐ Part-time farm work on land owned by me or rented from others
- ☐ Farm manager hired by someone else
- ☐ Retired
- ☐ Full-time off-farm work
- ☐ Part-time off-farm work

**11. In the past 12 months, which of the following outdoor activities have you participated in? (Check all that apply)**

- ☐ Fished in a lake, river, or creek
- ☐ Swam in a lake, river, or creek
- ☐ Explored or waded along a river or creek
- ☐ Kayaked or canoed
- ☐ Hiked or viewed wildlife
- ☐ Hunted
- ☐ Had a picnic in the outdoors
- ☐ Used a bike trail
- ☐ Went horseback riding
- ☐ Went off-roading

**12. Based on what you know and can observe about the Minnesota River Basin, do you think there are significant water-related problems associated with it? (Check one)**

- ☐ Yes
- ☐ No
- ☐ Don't know

**13. What do you think about water-related environmental problems in the Basin?(Check all that apply)**

- ☐ High level of sediment in the river
- ☐ High level of nutrients in the river
- ☐ Trash in the river and along the bank
- ☐ Odor from the river
- ☐ Lack of fish or aquatic life
- ☐ Unsafe to swim or wade in the river
- ☐ Unnatural colors of the water and rocks along the river
- ☐ Unsafe drinking water from wells

| | Not At All Familiar | Slightly Familiar | Moderately Familiar | Very Familiar | Extremely Familiar |
|---|---|---|---|---|---|
| **14. How familiar are you with the "25 by 25" water quality goal for Minnesota State?** | ☐ | ☐ | ☐ | ☐ | ☐ |

## Part II. Minnesota River Basin Conditions

*Funds to improve water quality can be targeted to somewhat different goals. We want to know which goals are important to you. We ask that you think about different water quality* ***goals*** *and corresponding* ***improvements*** *in the Minnesota River Basin.*

### Goal 1: Scenic Quality

This goal measures the natural beauty of Minnesota River Basin.

| | Not At All Concerned | Slightly Concerned | Moderately Concerned | Very Concerned | Extremely Concerned |
|---|---|---|---|---|---|
| **15. How concerned are you about the current scenic quality of waterways in Minnesota River Basin?** | ☐ | ☐ | ☐ | ☐ | ☐ |

**Moderate Improvement - No Litter**

Regular removal of all trash occurs from the stream and banks.

| | Not At All Important | Slightly Important | Moderately Important | Very Important | Extremely Important |
|---|---|---|---|---|---|
| **16. How important is the achievement of moderate improvements in scenic quality to you?** | ☐ | ☐ | ☐ | ☐ | ☐ |

**Major Improvement - Basin Beautification and No Litter**

Regular removal of all trash occurs from the stream and banks **plus** beautification. Beautification would include trash receptacles along trails, vegetative and flower planting, and bank erosion control.

| | Not At All Important | Slightly Important | Moderately Important | Very Important | Extremely Important |
|---|---|---|---|---|---|
| **17. How important is the achievement of moderate improvements in scenic quality to you?** | ☐ | ☐ | ☐ | ☐ | ☐ |

## Goal 2: Nutrient Reduction

This goal measures the reduction of nutrient pollution in the water, such as nitrogen and phosphorus.

| | Not At All Concerned | Slightly Concerned | Moderately Concerned | Very Concerned | Extremely Concerned |
|---|---|---|---|---|---|
| **18. How concerned are you about the current levels of nutrient pollution in Basin's waters?** | ☐ | ☐ | ☐ | ☐ | ☐ |

**Moderate Improvement - 25% reduction - Commit to a statewide goal**

In-state lake and river standards define the magnitude of needed nutrient reductions as 25% by 2025.Leads to some reduction in the Gulf of Mexico's annual summer hypoxia ("Dead Zone").

| | Not At All Important | Slightly Important | Moderately Important | Very Important | Extremely Important |
|---|---|---|---|---|---|
| **19. How important is the achievement of a moderate reduction in nutrient levels to you?** | ☐ | ☐ | ☐ | ☐ | ☐ |

**Major Improvement - 45% reduction - Contribute to downstream water quality and the Gulf of Mexico hypoxia goal**

Minnesota attains a 45% reduction in nitrogen and phosphorus flowing down the Mississippi River by 2025, exceeding the statewide goal. If other states (e.g., Iowa, Illinois, Indiana) follow suite, likely attain the goal of reducing the size of Gulf of Mexico hypoxia by 67%.

| | Not At All Important | Slightly Important | Moderately Important | Very Important | Extremely Important |
|---|---|---|---|---|---|
| **20. How important is the achievement of a major reduction in nutrient levels to you?** | ☐ | ☐ | ☐ | ☐ | ☐ |

## Goal 3: Aquatic Life & Wildlife Habitat

This goal measures how well the Basin supports aquatic life (e.g. fish) and other wildlife (e.g. ducks).

| | Not At All Concerned | Slightly Concerned | Moderately Concerned | Very Concerned | Extremely Concerned |
|---|---|---|---|---|---|
| **21. How concerned are you about the current ability of the Basin to provide high-quality habitat?** | ☐ | ☐ | ☐ | ☐ | ☐ |

**Moderate Improvement - Partially Support**

Water quality improves enough for moderate support of aquatic life and wildlife. More places for good bird-watching or hunting in the Basin.

| | Not At All Important | Slightly Important | Moderately Important | Very Important | Extremely Important |
|---|---|---|---|---|---|
| **22. How important is the achievement of a moderate improvement in habitat quality to you?** | ☐ | ☐ | ☐ | ☐ | ☐ |

**Major Improvement - Fully Support**

Water quality and stream habitat are improved such that sustained, reproducing populations of aquatic life and wildlife are established. Spectacular bird watching and hunting are available throughout the Basin.

| | Not At All Important | Slightly Important | Moderately Important | Very Important | Extremely Important |
|---|---|---|---|---|---|
| **23. How important is the achievement of a major improvement in habitat quality to you?** | ☐ | ☐ | ☐ | ☐ | ☐ |

## Goal 4: Sediment Reduction

This attribute measures the reduction of sediment pollution.

| | Not At All Concerned | Slightly Concerned | Moderately Concerned | Very Important | Extremely Concerned |
|---|---|---|---|---|---|
| **24. How concerned are you about the current levels of sediment in Basin's waters?** | ☐ | ☐ | ☐ | ☐ | ☐ |

**Moderate Improvement - 40% reduction**

Focus on the target of 40% sediment reduction by 2025.

| | Not At All Important | Slightly Important | Moderately Important | Very Important | Extremely Important |
|---|---|---|---|---|---|
| **25. How important is the achievement of a moderate reduction in sediment levels to you?** | ☐ | ☐ | ☐ | ☐ | ☐ |

**Major Improvement - 80% reduction**

Aggressive focus on 80% sediment reduction by 2025.

| | Not At All Important | Slightly Important | Moderately Important | Very Important | Extremely Important |
|---|---|---|---|---|---|
| **26. How important is the achievement of a major reduction in sediment levels to you?** | ☐ | ☐ | ☐ | ☐ | ☐ |

## Goal 5: Aquatic Recreation

This goal measures how safe and enjoyable aquatic recreation is in the waters of the Minnesota River Basin.

| | Not At All Concerned | Slightly Concerned | Moderately Concerned | Very Concerned | Extremely Concerned |
|---|---|---|---|---|---|
| **27. How concerned are you about your current ability to safely and enjoyably engage in aquatic recreation in the Basin's waters?** | ☐ | ☐ | ☐ | ☐ | ☐ |

**Moderate Improvement - Partially Support**

The rivers meet the water quality standards for safe secondary body contact recreation (e.g. boating and wading). Discharges of sediment and sewage are treated prior to release. The water is no longer toxic, but staining and discoloration from river water may still occur.

| | Not At All Important | Slightly Important | Moderately Important | Very Important | Extremely Important |
|---|---|---|---|---|---|
| **28. How important is the achievement of a moderate improvement in the recreation potential of Basin's waters to you?** | ☐ | ☐ | ☐ | ☐ | ☐ |

**Major Improvement - Fully support**

Water is safe for primary body contact recreation (e.g. swimming and other recreation where immersion and inadvertently ingesting water is likely). No untreated sewage from any source is discharged into the river. No staining and discoloration occur.

| | Not At All Important | Slightly Important | Moderately Important | Very Important | Extremely Important |
|---|---|---|---|---|---|
| **29. How important is the achievement of a major improvement in the recreation potential of Basin's waters to you?** | ☐ | ☐ | ☐ | ☐ | ☐ |

## Part III. Management Options For Your Land

Based on research conducted by local scientists and local stakeholder feedback, we identified promising land management practices to reduce water pollution:

**Management Options Category**

- **Wetland Restoration:**

  Restored wetlands are designed to receive polluted water from tile drain outlets or small ditches, and they hold and clean the water before it is discharged downstream.

- **Cover Crops:**

  Cover crops (e.g. annual and cereal rye-grass, wheat, oat, forage radish) can capture pollutants during winter when fields are out of vegetation and can be prone to pollutant losses.

- **Nutrient Management:**

  Adopting a nutrient management plan involves developing and following a yearly plan with soil tests conducted to determine the nutrient needs of crops.

(After you finish reading, please directly go to Part IV.)

## Part IV. Choice Experiment (these questions are of particular importance to us)

As you can imagine, there are many ways to manage your land to improve water quality in the Basin. We are presenting some of those possibilities for your consideration. Your choices will reflect the opinion of landowners in the Basin and may influence the overall direction of Minnesota River Basin water quality efforts.

- The next 8 questions will present you with such options. The **"Voluntary Conservation Option"** will present different land management practices you would choose to adopt on your land, as well as the annual per-acre incentive payment you would receive.
- You may also choose the **"Current Condition"** option, where no additional water quality improvements occur and you do not receive payments for additional management practices.
- Given that State funding is limited, we expect that not all willing landowners would be able to receive incentive payments.
- In evaluating the options below, please imagine that the State will first make preliminary offers of management practices/payment combinations, similar to the voluntary conservation options below.
- Landowners willing to accept such offers will compete for limited funding.
- Funding will go to the most competitive offers, based on estimated water quality benefit per dollar.
- Offers are specified on a per acre basis (with the understanding that while restoring wetlands takes land out of production, cover crops and nutrient management do not).
- Assume that payments continue as long as management practices are in place, and landowner retains all land rights (no easement is created).
- Please consider the annual payment listed below as the only compensation for management practices.

### Choice 1

**30. Please consider the options below. Please answer this question without consideration of the other 7 choice questions. Of the presented options, you would choose:**

☐ Voluntary Conservation Option ☐ Current Condition

| **Land Management Practices** | **Voluntary Conservation Option** | **Current Condition** |
|---|---|---|
| Wetlands Restoration | YES | NO |
| Cover Crops | YES | NO |
| Nutrient Management Plan | YES | NO |
| **Annual Payment ($/acre)** | 600 | 0 |

### Choice 2

**31. Please consider the options below. Please answer this question without consideration of the other 7 choice questions. Of the presented options, you would choose:**

☐ Voluntary Conservation Option ☐ Current Condition

| **Land Management Practices** | **Voluntary Conservation Option** | **Current Condition** |
|---|---|---|
| Wetlands Restoration | NO | NO |
| Cover Crops | YES | NO |
| Nutrient Management Plan | NO | NO |
| **Annual Payment ($/acre)** | 50 | 0 |

### Choice 3

**32. Please consider the options below. Please answer this question without consideration of the other 7 choice questions. Of the presented options, you would choose:**

☐ Voluntary Conservation Option ☐ Current Condition

| **Land Management Practices** | **Voluntary Conservation Option** | **Current Condition** |
|---|---|---|
| Wetlands Restoration | YES | NO |
| Cover Crops | NO | NO |
| Nutrient Management Plan | NO | NO |
| **Annual Payment ($/acre)** | 650 | 0 |

### Choice 4

**33. Please consider the options below. Please answer this question without consideration of the other 7 choice questions. Of the presented options, you would choose:**

☐ Voluntary Conservation Option ☐ Current Condition

| **Land Management Practices** | **Voluntary Conservation Option** | **Current Condition** |
|---|---|---|
| Wetlands Restoration | NO | NO |
| Cover Crops | NO | NO |
| Nutrient Management Plan | YES | NO |
| **Annual Payment ($/acre)** | 25 | 0 |

### Choice 5

**34. Please consider the options below. Please answer this question without consideration of the other 7 choice questions. Of the presented options, you would choose:**

☐ Voluntary Conservation Option ☐ Current Condition

| **Land Management Practices** | **Voluntary Conservation Option** | **Current Condition** |
|---|---|---|
| Wetlands Restoration | YES | NO |
| Cover Crops | YES | NO |
| Nutrient Management Plan | YES | NO |
| **Annual Payment ($/acre)** | 500 | 0 |

### Choice 6

**35. Please consider the options below. Please answer this question without consideration of the other 7 choice questions. Of the presented options, you would choose:**

☐ Voluntary Conservation Option ☐ Current Condition

| **Land Management Practices** | **Voluntary Conservation Option** | **Current Condition** |
|---|---|---|
| Wetlands Restoration | NO | NO |
| Cover Crops | NO | NO |
| Nutrient Management Plan | YES | NO |
| **Annual Payment ($/acre)** | 450 | 0 |

### Choice 7

**36. Please consider the options below. Please answer this question without consideration of the other 7 choice questions. Of the presented options, you would choose:**

☐ Voluntary Conservation Option ☐ Current Condition

| **Land Management Practices** | **Voluntary Conservation Option** | **Current Condition** |
|---|---|---|
| Wetlands Restoration | NO | NO |
| Cover Crops | YES | NO |
| Nutrient Management Plan | NO | NO |
| **Annual Payment ($/acre)** | 150 | 0 |

### Choice 8

**37. Please consider the options below. Please answer this question without consideration of the other 7 choice questions. Of the presented options, you would choose:**

☐ Voluntary Conservation Option ☐ Current Condition

| **Land Management Practices** | **Voluntary Conservation Option** | **Current Condition** |
|---|---|---|
| Wetlands Restoration | YES | NO |
| Cover Crops | NO | NO |
| Nutrient Management Plan | NO | NO |
| **Annual Payment ($/acre)** | 200 | 0 |

## Part V. Land Management Options Valuation

*We would like to ask you about your experience with, and opinions about, different management practices.*

### Wetland Restoration

**38a. Are you open to restoring wetlands on your land? Selecting "No" means that you won't implement this management practice no matter the amount of incentive payment offered**

☐ Yes ☐ No ☐ Undecided

**38b. Have you restored or protected wetlands on your land?**

☐ Yes, I have restored wetlands on my land

☐ Yes, I have protected existing wetlands on my land

☐ No

**38c. Do you personally know anyone who restored wetlands on their land?**

☐ Yes ☐ No

| | Not At All Familiar | Slightly Familiar | Moderately Familiar | Very Familiar | Extremely Familiar |
|---|---|---|---|---|---|
| **38d. How familiar are you with the process and the costs of wetland restoration?** | ☐ | ☐ | ☐ | ☐ | ☐ |

| | Strongly Disagree | Disagree | Undecided | Agree | Strongly Agree |
|---|---|---|---|---|---|
| **38e. The cost of restoring wetlands is too high.** | ☐ | ☐ | ☐ | ☐ | ☐ |
| **38f. Restoring wetlands causes loss of control over one's land, even if no easement is created.** | ☐ | ☐ | ☐ | ☐ | ☐ |
| **38g. It is difficult to move equipment in the field with restored wetlands.** | ☐ | ☐ | ☐ | ☐ | ☐ |
| **38h. The cost and effort of maintaining wetlands is too high.** | ☐ | ☐ | ☐ | ☐ | ☐ |
| **38i. Wetlands are key to maintaining high quality wildlife habitat.** | ☐ | ☐ | ☐ | ☐ | ☐ |
| **38j. Wetlands protect water quality by catching soil and nutrients before they flow into streams.** | ☐ | ☐ | ☐ | ☐ | ☐ |

### Cover Crops

**39a. Are you open to planting cover crops on your land? Selecting "No" means that you won't implement this management practice no matter the amount of incentive payment offered.**

☐ Yes ☐ No ☐ Undecided

**39b. In the past 5 years, have you planted cover crops on your land?**

☐ Yes, but I no longer plant cover crops

☐ Yes, and I plan to continue planting cover crops

☐ No.

**39c. Do you personally know anyone who is planting cover crops on a regular basis?**

☐ Yes ☐ No

| | Not At All Familiar | Slightly Familiar | Moderately Familiar | Very Familiar | Extremely Familiar |
|---|---|---|---|---|---|
| **39d. How familiar are you with cover crops?** | ☐ | ☐ | ☐ | ☐ | ☐ |

| | Strongly Disagree | Disagree | Undecided | Agree | Strongly Agree |
|---|---|---|---|---|---|
| **39e. Cover crops reduce yields of primary crops.** | ☐ | ☐ | ☐ | ☐ | ☐ |

| | | | | | |
|---|---|---|---|---|---|
| **39f.** | **It takes too much time to plant a cover crops after harvest in the fall.** | Strongly Disagree ☐ | Disagree ☐ | Undecided ☐ | Agree ☐ | Strongly Agree ☐ |
| **39g.** | **It takes too much time to harvest or kill cover crops before planting in the spring.** | Strongly Disagree ☐ | Disagree ☐ | Undecided ☐ | Agree ☐ | Strongly Agree ☐ |
| **39h.** | **Cover crops reduce soil loss from fields.** | Strongly Disagree ☐ | Disagree ☐ | Undecided ☐ | Agree ☐ | Strongly Agree ☐ |
| **39i.** | **Cover crops improve soil quality.** | Strongly Disagree ☐ | Disagree ☐ | Undecided ☐ | Agree ☐ | Strongly Agree ☐ |
| **39j.** | **Cover crops lower the input of nutrients for crops.** | Strongly Disagree ☐ | Disagree ☐ | Undecided ☐ | Agree ☐ | Strongly Agree ☐ |

### Nutrient Management

**40a. Are you open to adopting a nutrient management plan for your land? Selecting “No” means that you won’t implement this management practice no matter the amount of incentive payment offered.**

☐ Yes ☐ No ☐ Undecided

**40b. Do you currently have a nutrient management plan in place?**

☐ Yes ☐ No

**40c. Do you personally know anyone who has a written nutrient management plan in place?**

☐ Yes ☐ No

| | | | | | | |
|---|---|---|---|---|---|---|
| **40d.** | **How familiar are you with nutrient management plans?** | Not At All Familiar ☐ | Slightly Familiar ☐ | Moderately Familiar ☐ | Very Familiar ☐ | Extremely Familiar ☐ |
| **40e.** | **Nutrient management plan reduces crop yields in the short term.** | Strongly Disagree ☐ | Disagree ☐ | Undecided ☐ | Agree ☐ | Strongly Agree ☐ |
| **40f.** | **Nutrient management plan reduces crop yields in the long term.** | Strongly Disagree ☐ | Disagree ☐ | Undecided ☐ | Agree ☐ | Strongly Agree ☐ |
| **40g.** | **Nutrient management plan improves soil quality.** | Strongly Disagree ☐ | Disagree ☐ | Undecided ☐ | Agree ☐ | Strongly Agree ☐ |
| **40h.** | **Nutrient management plans reduce fertilizer costs.** | Strongly Disagree ☐ | Disagree ☐ | Undecided ☐ | Agree ☐ | Strongly Agree ☐ |
| **40i.** | **The cost for nutrient management plan is too high** | Strongly Disagree ☐ | Disagree ☐ | Undecided ☐ | Agree ☐ | Strongly Agree ☐ |

## Part VI Watershed Conservation Valuation

**On a scale of 1 to 5, please indicate your level of agreement or disagreement with the following statement**

| | | | | | | |
|---|---|---|---|---|---|---|
| **41a.** | **I know what steps to take to conserve soil and water on my land.** | Strongly Disagree ☐ | Disagree ☐ | Undecided ☐ | Agree ☐ | Strongly Agree ☐ |
| **41b.** | **I think farmers take undue blame for environmental problems in the watershed.** | Strongly Disagree ☐ | Disagree ☐ | Undecided ☐ | Agree ☐ | Strongly Agree ☐ |
| **41c.** | **I think soil and water conservation are important.** | Strongly Disagree ☐ | Disagree ☐ | Undecided ☐ | Agree ☐ | Strongly Agree ☐ |

| | | | | | |
|---|---|---|---|---|---|
| **41d. I think farming practices and land use (such as planting grass along streams or steep slopes) should be regulated to reduce pollution to surface water.** | Strongly Disagree ☐ | Disagree ☐ | Undecided ☐ | Agree ☐ | Strongly Agree ☐ |
| **41e. I think water contamination (from fertilizers, sediments, and septics) is an important environment problems in our watershed.** | Strongly Disagree ☐ | Disagree ☐ | Undecided ☐ | Agree ☐ | Strongly Agree ☐ |
| **41f. I think commodity payments impact my decisions about soil and water conservation.** | Strongly Disagree ☐ | Disagree ☐ | Undecided ☐ | Agree ☐ | Strongly Agree ☐ |
| **41g. I think farmers and other watershed residents should work together to protect watershed.** | Strongly Disagree ☐ | Disagree ☐ | Undecided ☐ | Agree ☐ | Strongly Agree ☐ |
| **41h. I think farmers and conservation agency staff should work together to protect watershed.** | Strongly Disagree ☐ | Disagree ☐ | Undecided ☐ | Agree ☐ | Strongly Agree ☐ |
| **41i. I consider myself as a steward of the land.** | Strongly Disagree ☐ | Disagree ☐ | Undecided ☐ | Agree ☐ | Strongly Agree ☐ |
| **41j. I think my responses to the survey will influence future decisions regarding water conservation policies.** | Strongly Disagree ☐ | Disagree ☐ | Undecided ☐ | Agree ☐ | Strongly Agree ☐ |

**42. Who do you think should be responsible for soil and water conservation in the watershed?(Check all that apply.)**

- ☐ Landowners
- ☐ Farm Managers
- ☐ Government conservation staff
- ☐ Renters
- ☐ Minnesota River Basin Board
- ☐ Other (please specify):________________

**43. What is an important source of information on conservation issues for you? (Check all that apply)**

- ☐ Natural Resources Conservation Service
- ☐ Farm Service Agency
- ☐ County Extension Service
- ☐ Specialists from local institutes
- ☐ Local seed/chemical/fertilizer dealers
- ☐ Machinery dealers
- ☐ Neighbors and friends
- ☐ Soil Conservation District Commissioners
- ☐ Vocational Agriculture Instructors
- ☐ Private Consultants
- ☐ Non-profit organizations, e.g. the Nature Conservancy
- ☐ Other (please specify):________________

**44. How do you prefer to receive information about conservation issues?(Check all that apply)**

- ☐ Field demonstrations (tours)
- ☐ County and local meetings
- ☐ Magazines
- ☐ Printed Materials (brochures)
- ☐ On-farm consultation
- ☐ Internet, Webcasts, Podcasts
- ☐ Television programs
- ☐ Radio
- ☐ Visual materials (slides, photographs)
- ☐ Trade shows and fairs
- ☐ Other (please specify):____________________

## Part VI. Additional Information

**45. What is your gender?** ☐ Male ☐ Female

**46. What is your age?** ☐ Under 30 ☐ 30-50 ☐ 50-70 ☐ Over 70

**47. What is the highest level of formal education you have achieved?**

- ☐ High school diploma
- ☐ Some college but no 4-year degree
- ☐ B.A., B.S., or equivalent
- ☐ Graduate degree

**48. Considering all sources of agricultural income (including government payments), what was the total gross value of your agricultural income in 2017?**

- ☐ None
- ☐ $1 -$24,999
- ☐ $25,000 - $99,999
- ☐ $100,000 - $249,999
- ☐ $250,000 - $499,999
- ☐ $500,000 to $999,999
- ☐ $1,000,000 and over

## THANK YOU FOR YOUR PARTICIPATION!

***If you have any comments, please feel free to add them here:***